Protected Area Performance in the Dry Forests and Savannahs of West Africa: a Study using L-band Synthetic Aperture Radar

Submitted by Andrew Cox to the University of Exeter
as a dissertation for the degree of
Master of Science by Research in Geography
In January 2019

I certify that all material in this dissertation which is not my own work has been identified and that any material that has previously been submitted and approved for the award of a degree by this or any other University has been acknowledged.

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ABSTRACT

Tropical ecosystems harbour the highest concentrations of biodiversity on Earth and play a pivotal role in the global carbon cycle, yet deforestation and degradation continue unabated in many regions, with net forest loss at 5.5 million ha yr^{-1} between 2010 and 2015. Protected areas offer a partial solution to this problem, with a growing body of evidence demonstrating their effectiveness for habitat conservation in the dense forests of Amazonia, Central Africa and Southeast Asia. Despite containing over a quarter of global biodiversity hotspots and being low density but significant carbon stores, tropical drylands have received far less attention in conservation terms, and research into protected areas in these ecosystems is far more limited. The overall effectiveness of protected areas in different dryland regions, and the factors influencing performance, are less understood. By measuring protected area performance as a function of aboveground biomass change, this study investigated the effectiveness of protected areas in the savannah belt of Nigeria, a country with a long history of environmental degradation. L-band Synthetic Aperture Radar (SAR), a form of remote sensing that penetrates the vegetation canopy, provided a means of consistently monitoring aboveground biomass change over time. Twenty-one areas, ranging in size from 117,000 ha to 608,410 ha, and offering varying levels of protection according to IUCN designations, were selected, with aboveground biomass changes between 2007 and 2017 determined by subjecting L-band SAR data to a novel approach called ‘Biomass Matching’. The combination of SAR and Biomass Matching allowed aboveground biomass changes within these protected areas to be detected and estimated without the need for supplementary field data, which is usually required to calibrate such remote sensing data. All but four protected areas experienced increases in aboveground biomass over the study period, with mean change being +1.22 Mg ha^{-1}, compared to +0.26 Mg ha^{-1} for a set of twelve similar unprotected areas. Furthermore, their performance was affected by an array of factors, though accessibility and management efficacy were deemed the most influential. These results suggest that, with appropriate monitoring and resourcing, protected areas in Nigerian dry forests and savannahs can provide effective habitat conservation, though more inaccessible areas will inherently perform better.

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ABBREVIATIONS AND ACRONYMS

AGB = aboveground biomass

ALOS = Advanced Land Observing Satellite

AW3D30 = ALOS World 3D – 30m

BGB = belowground biomass

C = carbon

CA = control area

CH_4 = methane

CIESIN = Center for International Earth Science Information Network

CITES = Convention on International Trade in Endangered Species

CO_2 = carbon dioxide

DBH = diameter-at-breast-height

FAO = Food and Agriculture Organisation of the United Nations

GDP = gross domestic product

GHG = greenhouse gas

GIS = Geographic Information Systems

GPWv4 = Gridded Population of the World, Version 4

gROADSv1 = Global Roads Open Access Data Set, Version 1

HH = horizontal-send, horizontal receive

HV = Horizontal-send, vertical receive

IPCC = Intergovernmental Panel on Climate Change

IUCN = International Union for Conservation of Nature

JAXA = Japanese Aerospace Exploration Agency

LiDAR = light detection and ranging

LULCC = land-use and land-cover change

MODIS = Moderate Resolution Imaging Spectroradiometer

N_2O = nitrous oxide

NDC = Nationally Determined Contributions

PA = protected area

PADDD = protected area downgrading, downsizing and degazettement

PALSAR = Phased-array type L-band synthetic aperture radar

RCS = radar cross-section

SAR = synthetic aperture radar

SDG = Sustainable Development Goal

SEDAC = Socioeconomic Data and Applications Center

SRTM DEM = Shuttle Radar Tomography Mission digital elevation model

UN = United Nations

UNDP = United Nations Development Programme

UNEP-WCMC = United Nations Environment World Conservation Monitoring Centre

UNFCCC = United Nations Framework Convention on Climate Change

WDPA = World Database on Protected Areas

ACKNOWLEDGEMENTS

There are a number of people whom without, this piece of work would not have been possible. Enormous thanks go to Dr Tim Hill for his continued supervision and guidance throughout the process, and for allowing me to undertake this project in the first place – it's been a real privilege to have worked with you over the last 15-16 months, thank you so much for putting up with me! Thanks also go to many of my fellow PGRs in the Geography Postgraduate Office, for giving me advice along the way and for making the long hours of monotonous processing and fighting with unwieldy computer software far more bearable. Finally, I want to thank my parents for supporting my decision to carry out this investigation and to stay in higher education for a little longer than anticipated; I could not have reached the finish line without them.

Introduction

1.1 Tropical Ecosystems, Climate Change and the Paris Climate Agreement

Tropical ecosystems are a key constituent of the global carbon cycle, with approximately 55% of terrestrial carbon contained within tropical forests alone (Pan *et al*., 2011). This is apportioned between live biomass – both aboveground (AGB) in stems, branches and leaves, and belowground (BGB) in roots – soil, deadwood and litter. In the tropics, the majority of carbon is stored in living structures (Pan *et al*., 2011), with carbon constituting approximately 50% of live biomass (Brown and Lugo, 1982; Roy *et al*., 2001). Dense, intact forests are the primary component of this store (Malhi and Grace, 2000; Pan *et al*., 2011), but other tropical ecosystems make important contributions. For example, mangroves are incredibly high density but spatially-limited stores, holding around 1000 Mg C ha^{-1} (Donato *et al*., 2011), while dryland forests, which cover a similar area to their dense forest counterparts (Bastin *et al*., 2017) are a low density but extensive carbon sink. Tropical carbon storage is distributed across three main regions: tropical America, sub-Saharan Africa and Southeast Asia (Pan *et al*., 2011; Saatchi *et al*., 2011; Baccini *et al*., 2012; Avitabile *et al*., 2016), so estimating total tropical carbon stocks is extremely challenging. Field-based forest inventories and remote sensing are the primary means of gathering this information (FAO, 2015; Keenan *et al*., 2015), but differences in the data and exact methods used yield large disparities in estimates between studies (Mitchard *et al*., 2014; *Table 1.1*). Matters are further complicated by the uncertainties associated with different approaches: field-based methods directly measure AGB (and therefore, C), but are prone to human error and require upscaling, whereas remote sensing can estimate large-scale stocks but cannot directly measure AGB (Avitabile *et al*., 2016). However, regardless of such uncertainties, it is clear that the tropics are a globally significant carbon store.

As the majority of carbon in tropical ecosystems is contained in live biomass (Malhi and Grace, 2000; Pan *et al*., 2011), when these ecosystems are cleared or degraded the carbon within the stems, branches and roots of trees is released into the atmosphere as carbon dioxide (CO_2; Baccini *et al*., 2012). Consequently, tropical deforestation and degradation is a major source of global

CO_2 emissions. A net forest loss of 5.5 million ha yr^{-1} 2010-2015 (Keenan *et al*., 2015) would have substantially increased atmospheric greenhouse gas (GHG) concentrations, with many studies suggesting that tropical ecosystems are a net source of CO_2 emissions, ranging from 1.3±0.7 Gt C yr^{-1} (1990-2007; Pan *et al*., 2011), to 1.0 Gt C yr^{-1} (2000-2010; Baccini *et al*., 2012). Indeed, between 1850 and 2015, over 70% of land-use and land-cover change (LULCC) CO_2 emissions originated from tropical regions (Houghton and Nassikas, 2017). Despite this, the terrestrial biosphere as a whole is still responsible for sequestering around 30% of annual anthropogenic CO_2 emissions, a sink which

Table 1.1: Tropical Carbon Stocks. This shows estimated tropical carbon stocks (Gt C) in live biomass by a selection of studies. Differences in the data included and collection methods can yield markedly divergent results.

Study	**Tropical regions included**	**Data collection methods**	**Tropical carbon stocks – live biomass (Gt C)**
Avitabile *et al*. (2016)	Central and South America, Africa, South and Southeast Asia	Fusion of Saatchi *et al*. (2011) and Baccini *et al*. (2012) maps	187.5
Baccini *et al*. (2012)	Central and South America, Africa, South and Southeast Asia	Field-calibrated spaceborne LIDAR	228.7
Saatchi *et al*. (2011)	Central and South America, Africa, South and Southeast Asia (including Australia)	Field-calibrated spaceborne LIDAR	247
FAO (2011) – State of the World's Forests	Central and South America, Africa, South and Southeast Asia	National forest inventories	183.2
Feldpausch *et al*. (2012)	South America, Africa, Australia, Southeast Asia	Permanent forest sample plots	285
Köhl *et al*. (2015)	Central and South America, Africa, South and Southeast Asia	Estimates based on combining Saatchi *et al*. (2011) and Pan *et al*. (2011) data	298.4

is estimated to have increased in size from 1.4±0.7 G tC yr^{-1} in the 1960s, to 3.0±0.8 Gt C yr^{-1} between 2007 and 2016 (Le Quéré *et al*., 2018).

Understanding the potential for LULCC to act as both a source and sink of atmospheric carbon (Houghton *et al*., 1999; Le Quéré *et al*., 2009; Ballantyne *et al*., 2012; Sitch *et al*., 2015) is therefore becoming ever more important in the context of climate change.

The pertinent need to address the issue of 21st Century climate change is receiving increasing global recognition, most clearly exemplified by the 2015 Paris Climate Agreement (UNFCCC, 2015). The historic accord aimed to unite countries against the threat of climate change, 'keeping a global temperature rise this century well below 2ºC above pre-industrial levels and to pursue efforts to limit the temperature increase even further to 1.5ºC' - achieving this goal will require rigorous policy-making, and the implementation of effective mitigation strategies to greatly reduce current GHG emissions (UNFCCC, 2017). Failure to restrict global temperature rise could irreversibly modify the Earth system (Steffen *et al*., 2018) and present 'intolerable risks' to humanity (Schellnhuber *et al*., 2016). Indeed, there is growing evidence to suggest that even a 2ºC increase could have dangerous consequences (IPCC, 2018), increasing the severity of long-term impacts on both terrestrial (Jones *et al*., 2009; Lewis *et al*., 2011; Chadburn *et al*., 2017) and marine (Hoegh-Guldberg *et al*., 2007; Fabry *et al*., 2008) ecosystems. With only twelve years remaining to limit global temperature rise to 1.5ºC (IPCC, 2018), the demand for swift and effective climate action has never been greater.

Under the terms of the Paris Climate Agreement, the basis for countries implementing management strategies are the Nationally Determined Contributions (NDCs); many of these include considerable contributions from the land-use sector, which comprise a nation's agricultural and forestry activities (Grassi *et al*., 2017). Such activities may account for up to 10% of global CO_2 emissions annually (Le Quéré *et al*., 2015), as well as around a quarter of methane (CH_4) and Nitrous Oxide (N_2O) emissions (Tubiello *et al*., 2015). The expectation of many countries, particularly those in tropical regions, to meet their NDCs with key contributions from the land-use sector means that land-based climate mitigation and the concept of 'negative emissions' will comprise a vital component of the Paris Climate Agreement (Grassi *et al*., 2017; Houghton and Nassikas, 2017; Houghton and Nassikas, 2018). Indeed, such nations may achieve negative emissions through a number of means; these include significant reductions in rates of tropical deforestation and degradation, increasing the sustainability of timber harvesting and extraction, and encouraging forest regrowth and expansion (Houghton and Nassikas, 2018). Approaches to protecting and enhancing carbon stores in tropical ecosystems have long been recognised for their potentially significant contribution to combatting climate change (Gibbs *et al*., 2007; Scharlemann *et al*., 2010), and could offset up to 50% of annual anthropogenic CO_2 emissions, yielding results far more quickly than attempts to completely transition from fossil fuels to renewable energy (Houghton *et al*., 2015). The effective and responsible management of tropical ecosystems could therefore play an essential role in addressing the issue of climate change (Houghton *et al*., 2015; Grassi *et al*., 2017; Houghton *et al*., 2018).

Though not a universal solution to the problem of anthropogenic GHG emissions, enhancing carbon uptake and protecting stores in tropical ecosystems through effective land management could be significant in attempts to combat climate change (Gibbs *et al*., 2007; Scharlemann *et al*., 2010; Houghton *et al*., 2015; Grassi *et al*., 2017; Houghton *et al*., 2018). Indeed, protecting current stores in undisturbed, primary forests could be particularly important, as these ecosystems store large quantities of carbon and continue to accumulate it with age (Carey *et al*., 2001; Luyssaert *et al*., 2008; Stephenson *et al*., 2014). There are, however, significant political and economic obstacles which complicate the implementation of such strategies (Houghton *et al*., 2015), and thus considerable debate exists as to how these aims may best be achieved. Good evidence exists to suggest that, when effectively managed, protected areas are a valuable resource for conserving biodiversity and valuable ecosystem services, particularly carbon storage and sequestration (Juffe-Bignoli *et al*., 2014). Therefore, protected areas may contribute considerably to efforts to tackle tropical deforestation and degradation, and subsequently, offsetting anthropogenic GHG emissions and mitigating climate change.

1.2 <u>Protected Areas and Conservation</u>

1.2.1 <u>Protected Areas – an overview</u>

In practical terms, a protected area (PA) is ‘a clearly defined geographical space, recognised, dedicated and managed, through legal or other effective means, to achieve the long-term conservation of nature with associated ecosystem services and cultural values’ (Dudley, 2008). The extent of these areas across both the terrestrial surface and the world’s oceans has increased substantially in recent decades owing to the collective decisions of governments, publicly-funded bodies and local communities (Jenkins and Joppa, 2009; Watson *et al*., 2014), with official estimates refuting that around 209,000 PAs now encapsulate 15.4% of the terrestrial biosphere (excluding Antarctica) and 3.4% of the oceans (Juffe-Bignoli *et al*., 2014). PAs are central to global biodiversity targets, but their integration with the United Nation’s Sustainable Development Goals (SDGs) acknowledges the wider societal benefits they can provide, including fresh water provision (Postel and Thompson, 2005), food security (Lubchenco *et al*., 2003) and carbon storage (Dudley *et al*., 2014; Juffe-Bignoli *et al*., 2014). This growing reputation will almost certainly facilitate further expansion of the global PA network in years to come.

Despite their increasing contemporary importance, PAs have been present in various ‘unofficial’ forms for millennia; for example, as sacred sites for indigenous communities , or as hunting grounds maintained for the benefit of landowners and ruling classes (Chape *et al*., 2005; Watson *et al*., 2014). However, the modern movement only truly began in the 19th century, with PAs established in North America, Europe, Australia and South Africa to preserve places of outstanding natural beauty, or those harbouring rare and spectacular wildlife (Runte, 1977; Phillips, 2004). Though, initially, PAs were almost exclusively situated in landscapes of little economic potential, growing concern with the pace of environmental degradation and increased understanding of the importance of in-situ conservation resulted in a rapid expansion of PA networks during the 1970s (Phillips, 2004). There is now an expectation for them to achieve numerous ecological, social and economic objectives (Watson *et al*., 2014), in addition to their primary purpose of conserving and enhancing natural habitats.

The multi-faceted function of PAs has led to both international organisations and individual countries recognising their value (Leverington *et al*., 2010; Juffe-Bignoli *et al*., 2014; Watson *et al*., 2014). Consequently, many nations have declared ambitious protection targets (for example, China has pledged to increasing levels of PA coverage to 18% of its total area by 2050), are integrating PAs into their natural landscapes by establishing regional PA networks, and assessing ecological gaps within their existing networks in order to improve their performance (Ervin *et al*., 2008). As there is good evidence that properly managed PAs are an effective means of halting habitat clearance and degradation (Juffe-Bignoli *et al*., 2014), such commitments could be an essential component of climate change mitigation efforts (Leverington *et al*., 2010; Scharlemann *et al*., 2010; Soares-Filho *et al*., 2010; Watson *et al*., 2014). This is particularly true of PAs in dense tropical forests, which contain approximately 70.3 Gt C in live biomass and soil to a 1m depth, and between 2000 and 2005 lost half as much carbon as the same area of unprotected forest (Scharlemann *et al*., 2010). PAs are far from perfect: inadequate funding and policing can leave habitats within their borders vulnerable to anthropogenic disturbances (Leverington *et al*., 2010; Scharlemann *et al*., 2010; Watson *et al*., 2014), and conflicts with local peoples can arise when management goals do not align with community needs (Agrawal and Redford, 2009; Porter-Bolland *et al*., 2012). However, they generally present a fantastic mechanism for addressing a variety of problems, including the continuing deforestation and degradation of tropical ecosystems.

1.2.2 Tropical Protected Areas

In the tropics, PAs have become central in efforts to protect biodiversity and crucial ecosystem services from the continuing threats of deforestation and degradation, leading to an explosion of new tropical PAs in recent decades (Chape *et al*., 2005; Jenkins and Joppa, 2009; Laurance *et al*., 2012; Tranquilli *et al*., 2014). Jenkins and Joppa estimated that in 2009, 20.7% of tropical and subtropical moist broadleaf forests were protected; indeed, many countries in Central and South America have between a quarter and half of their total area under some form of protection, and, overall, these regions have 28.2% and 25% of their respective terrestrial areas protected to some degree (Deguignet *et al*., 2014). Much of the recent increase in South America’s – and in fact, global –

PA coverage has been centred in Amazonia (Jenkins and Joppa, 2009), and while this is largely a positive occurrence, there is a danger that other tropical regions and biomes may have been somewhat neglected. Compared to moist forests, only 8.1% of the tropical and subtropical dry broadleaf forest biome is under protection (Jenkins and Joppa, 2009), and other regions with substantial areas of both moist and dry forest exhibit far lower levels of terrestrial PA coverage: in Africa and Asia, this is 14.7% and 12.4% respectively (Deguignet *et al*., 2014). Although the extent of these networks is clearly important, it is the ability of individual PAs to prevent habitat clearance and degradation that is most valuable in the context of biodiversity conservation and climate change mitigation (Juffe-Bignoli *et al*., 2014) – a PA is of little use if it cannot adequately protect lands within its borders from external disturbances.

Despite the enormous potential of tropical PAs for addressing a variety of social and environmental issues (Bruner *et al*., 2001; Andam *et al*., 2008; Jenkins and Joppa, 2009; Laurance *et al*., 2012; Carranza *et al*., 2014; Geldmann *et al*., 2013; Bowker *et al*., 2017), they are far from untouchable, with many facing serious pressures which threaten to limit their overall effectiveness. The list is extensive: rapid population growth in many tropical regions has greatly heightened the risk of human encroachment (Tranquilli *et al*., 2014), environmental stressors – including changing precipitation patterns and alien species invasion – are becoming increasingly prevalent (Lovejoy, 2006; Watson *et al*., 2014), and attempts to exploit natural resources located within their borders are an ever-present problem (Laurance *et al*., 2012; Abernathy *et al*., 2013). Furthermore, their capacity to address such pressures can be severely hampered by shortcomings in resource allocation and general management, a situation that can arise from national and local governments disregarding PAs as economically-viable investments (Wilkie *et al*., 2001), or political instability and endemic corruption within these institutions limiting investment in the first place (Laurance *et al*., 2006). Therefore, it is vital to continually assess PA effectiveness (Juffe-Bignoli *et al*., 2014), and to understand how different factors may influence this.

1.2.3 Tropical Protected Areas – debates on effectiveness

Table 1.2: PA Performance across the Tropics. Various data sources and analytical approaches are represented. Positive of negative PA performance is determined by their effectiveness in relation to unprotected areas.

Study	Data Used	Analytical Approach	Protected Area Performance – Postive (P) or Negative (N)?
Joppa *et al*. (2008)	Past forest cover and present land-cover	Inside-outside comparisons	**P** – forest cover almost always higher inside PAs
Alo and Pontius Jr. (2008)	Landsat land-cover maps for years 1990 and 2000	GIS analysis of systematic land-cover transitions	**N** – forests in Ghanaian PAs systematically transition to bare ground
Clark *et al*. (2013)	Three independent land-cover datasets	Historical land-use change models	**N** – land-use change rates inside and outside PAs often indistinguishable in S. Asia
Andam *et al*. (2008)	Forest cover from aerial photography and Landsat	Matching methods	**P** – protection avoided 10% of potential deforestation in Costa Rica
Gaveau *et al*. (2009)	Forest cover from Landsat	Matching methods	**P** – deforestation rates lower in Sumatran PAs 1990-2000
Nelson and Chomitz (2011)	Fire data (as proxy for deforestation)	Matching methods	**P** – PAs significantly reduce fire incidence in tropical forests
Carranza *et al*. (2014)	Remote sensing deforestation data	Matching methods	**P** – all types of Cerrado PAs experienced lower conversion rates 2002-2009
Ament and Cumming (2016)	Land-cover data from Landsat	Matching methods	**P** – natural cover loss significantly less frequent inside S. African PAs 2000-2009
Bowker *et al*. (2017)	Landsat forest loss data	Matching methods	**P** – most African PAs experienced significantly lower forest loss 2000-2013

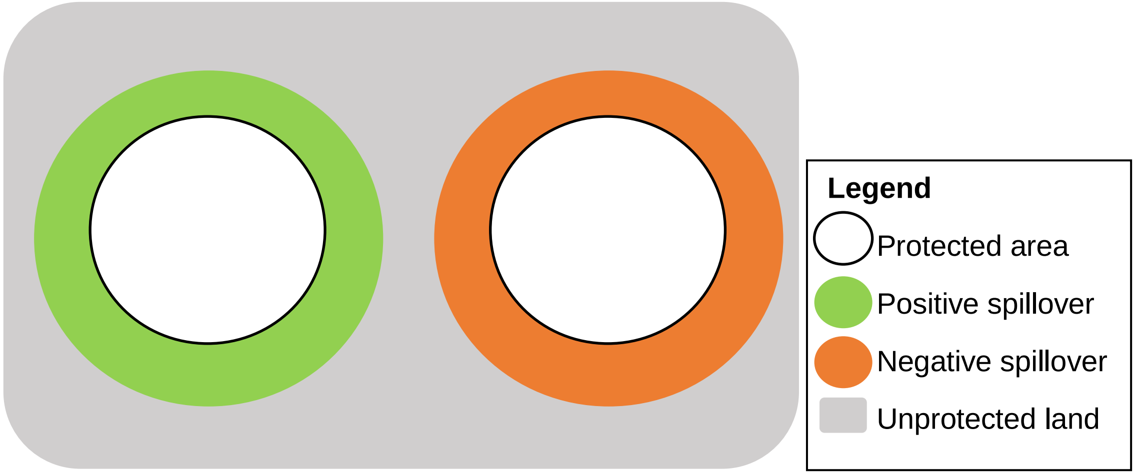


Fig 1.1: Positive and Negative Spillover Effects. The PA surrounded by a green buffer (left) shows how protective influence may extend beyond a PA's borders to give higher AGB levels than in the normal unprotected landscape (shaded in grey), while that surrounded by an orange buffer (right) shows how detrimental activities may be displaced to adjacent areas, resulting in lower AGB densities than surroundings.

Considerable evidence exists to suggest that PAs make substantial contributions to reducing deforestation and degradation in tropical regions. Forest cover within pan-tropical PAs has consistently been found to be higher than that of lands directly outside them (Nagrenda, 2008), and significantly so for the more accessible forests of West Africa and the Brazilian Atlantic Coast: 10km from PA boundaries, around 75% of West African and 50% of Atlantic Coast forests respectively have been cleared relative to that inside them (Joppa *et al*., 2008). However, such analytical approaches do not account for the positive or negative 'spillover' effects which may extend into unregulated lands adjacent to PAs (Andam *et al*., 2008; Ament and Cumming, 2016). Positive spillover is when the protective influence of a PA extends beyond its official borders, while negative spillover occurs when communities or human activities are displaced from within PAs to their immediate surroundings, causing habitat clearance (*Fig 1.1*; Andam *et al*., 2008; Ament and Cumming, 2016). In South Africa, such spillovers have been found to extend over 50km from PA boundaries (Ament and Cumming, 2016), and may bias assessments of their effectiveness. Therefore, to avoid including these effects and to account for the non-random distribution of PAs across landscapes, 'matching' methods are increasingly used to assess effectiveness: here, the PAs being analysed are compared to randomly generated control areas (CAs) possessing similar contextual characteristics, delivering objective and unbiased results (Gaveau *et al*., 2009; Joppa and Pfaff, 2010; Nelson and Chomitz, 2011; Carranza *et al*., 2014; Blackman *et al*., 2015; Bowker *et al*., 2017). Such methods regularly reach positive conclusions regarding tropical PA performance (*Table 1.2*), supporting the notion that they are an effective means of habitat conservation.

Alternatively, there are those who question the ability of tropical PAs to prevent deforestation and degradation, presenting results to suggest that forest loss inside their borders can equal or even exceed that occurring outside (Alo and Pontius Jr., 2008; Pfeifer *et al*., 2012; Clark *et al*., 2013). In some circumstances, forests within PAs may be at greater risk of clearance from logging and timber harvesting than areas outside, as these may already have been converted to agriculture (Alo and Pontius Jr., 2008), while in other regions, habitat conversion rates inside PAs may be indistinguishable from those taking place on nearby unprotected lands (Clark *et al*., 2013). However, such adverse findings may originate from the unique methodologies used to assess PA performance (*Table 1.2*), so differing conclusions from investigations which use matching methods may be expected. However, an increasingly prevalent and recognised hindrance to effectiveness is the phenomenon of protected area downgrading, downsizing, and degazettement (PADDD): PAs may legally have their protection levels lessened (downgrading), be legally reduced in size (downsizing), or even have all legal protection eliminated (degazettement; Mascia and Pailler, 2011; Symes *et al*., 2016). Such events challenge previous assumptions of PA permanence, and for many years were severely under-reported (Mascia and Pailler, 2011; Symes *et al*., 2016), though now evidence for continuing and even increasing occurrences of PADDD in certain parts of the world (De Marques and Peres, 2014) present significant threats to the efficacy of PAs for preventing deforestation and degradation.

1.2.4 <u>Tropical Protected Areas – factors influencing effectiveness</u>

While it is important to consider the effectiveness of tropical PAs in relation to unprotected lands, individual PA performance is determined by a multitude of factors; therefore, comparing PAs against one another is also essential when assessing their contributions to habitat conservation. For example, Bowker *et al*. (2017) find that the Democratic Republic of Congo and Tanzania are home to some of the most and least effective PAs in tropical Africa, so national-level governance alone cannot explain PA performance in this region. Instead, it will be the function of various drivers: perhaps many of the more effective PAs have been designated stricter protection under the International Union for Conservation of Nature (IUCN) classifications (Bruner *et al*., 2001; Scharlemann *et al*., 2010; Pfeifer *et al*., 2012; Nolte *et al*., 2013; Schafer, 2015), while those which have experienced greater internal forest loss are in less remote locations, and hence more accessible to anthropogenic disturbances (Joppa and Pfaff, 2009; Freitas *et al*., 2010; Nelson and Chomitz, 2011; Nolte *et al*., 2013; Pfaff *et al*., 2014; Bowker *et al*., 2017). To complicate matters, these drivers frequently interact with one another, making it difficult to assess their individual impacts on PA effectiveness. Therefore, the following paragraphs will discuss the relative influence of different factors on PA performance (*Table 1.3*) and allude to the potential importance of any interrelationships between them.

Table 1.3: Factors Influencing Tropical PA Effectiveness. These are the factors most regularly cited by studies investigating the drivers of tropical PA effectiveness. The general consensus of how each factor is perceived to influence performance is

Factor influencing PA performance	Included in studies…	Direction of relationship – positive/negative/contested
Size	Bruner *et al*. (2001), Blackman *et al*., (2015), Bowker *et al*. (2017), Struhsaker *et al*. (2005), Joppa *et al*. (2008), Symes *et al*. (2016)	**Contested** – size may interact with other factors to enhance PA performance, but may also increase likelihood of PADDD
Age	Eagles *et al*. (2002), Dudley *et al*. (2007), Andrade and Rhodes (2012), Blackman *et al*., (2015), Bowker *et al*. (2017)	**Contested** – improved reputation over time may increase resourcing and community compliance, but recent establishment may also do this
Level of Protection (according to IUCN classification)	Bruner *et al*. (2001), Nagrenda (2008), Scharlemann *et al*. (2010), Pfeifer *et al*. (2012), Nolte *et al*. (2013), Schafer (2015), Nelson and Chomitz (2011), Porter-Bolland *et al*. (2012) Blackman *et al*. (2015), Ferraro *et al*. (2013) Pfaff *et al*. (2014)	**Contested** – some consider stricter protection to offer better habitat conservation, while others argue that mixed-use areas can be equally or even more effective

Governance Regimes and Resourcing	Blackman *et al*. (2015), Symes *et al*. (2016), De Marques and Peres (2014), Leverington *et al*. (2010), Laurance *et al*. (2012), Tranquilli *et al*. (2014), Jachmann (2008), Watson *et al*. (2014)	**Positive** – effective governance and greater resourcing will lessen habitat clearance and degradation
Accessibility	Joppa and Pfaff (2009), Nelson and Chomitz (2011), Freitas *et al*. (2013), Nolte *et al*. (2013), Pfaff *et al*. (2014), Bowker *et al*. (2017)	**Negative** – more accessible PAs will be at greater risk of habitat clearance and degradation

The strictness of protection afforded to PAs in the tropics (and worldwide) is far from uniform, with a spectrum of management categories and designations applicable which are derived from both IUCN specifications and national authorities (Burgess *et al*., 2005; Dudley, 2008). The IUCN (Dudley, 2008) provides a ranking system to translate local descriptions of management rigorousness into a universal categorisation, ranging from 1a (the highest level of protection) to VI (the lowest); more restrictive governance is often associated with categories 1a – IV, while V and VI are less restrictive and permit sustainable use of natural resources (Pfaff *et al*., 2014), though interpretations differ between studies (see Nelson and Chomitz (2011) and Blackman *et al*. (2015) for examples). Areas afforded IUCN categorisations are generally managed by wildlife conservation authorities, though there are also those managed by forest authorities (i.e. Forest Reserves) which were specifically established for controlled resource utilisation, and hence cannot 'officially' be considered PAs (Burgess *et al*., 2005). Mirroring this variability in levels of protection, there is considerable debate as to which designations exert the greatest influence on PA effectiveness, particularly regarding habitat conservation. Consistent with what might be expected, some studies suggest that stricter PAs – such as National Parks (IUCN II) and Strict Nature Reserves (IUCN 1a) – offer the greatest conservation benefits (Bruner *et al*., 2001; Scharlemann *et al*., 2010; Pfeifer *et al*., 2012; Nolte *et al*., 2013; Schafer, 2015). Conversely, others argue that mixed-use landscapes (IUCN V and VI, and sometimes IV) – such as indigenous lands and community-managed forests – can be an equally, or even more, effective means of habitat protection, whilst simultaneously offering economic and social benefits to local people (Nelson and Chomitz, 2011; Porter-Bolland *et al*., 2012; Blackman *et al*., 2015). Frequently, however, the situation is more complex: the overall impact on deforestation and degradation of different management categories and designations is variable between countries and regions (Nelson and Chomitz, 2011; Ferraro *et al*., 2013; Pfaff *et al*., 2014), and at times these may fail completely to explain differences in PA effectiveness (Nagrenda, 2008). Such arguments suggest that, although a PA's level of protection is often influenced by its categorisation, it is likely also a product of the resourcing it receives from local and national authorities, and the commitment of these to wildlife and habitat conservation.

The effect of governance regimes on PA performance is a similarly complicated matter, intricately linked to the management and resourcing they receive. A logical assumption would be that wealthier national governments and local authorities, committed to conservation and climate change targets, are less likely to permit potentially destructive activities within their PAs (Symes *et al*., 2016), whilst simultaneously allocating them sufficient funding for monitoring and law enforcement purposes (Blackman *et al*., 2015). However, a country's wealth is rarely an adequate indicator of PA performance: PAs in less developed tropical nations can sometimes be particularly effective in efforts to reduce deforestation and degradation (Nagrenda, 2008), whereas more affluent countries which have made impressive advances in reducing forest clearance, such as Brazil (Nepstad *et al*., 2009; Arima *et al*., 2014), can still be hindered by corrupt authorities or allow PADDD to satisfy certain economic and infrastructural demands (De Marques and Peres, 2014). Therefore, it could be argued that, when governance is concerned, a general commitment to conservation and adequate resource provision are the most important determinants of PA effectiveness (Bruner *et al*., 2001; Watson *et al*., 2014). Indeed, resourcing can directly link to various parameters which may influence PA performance, including boundary demarcation, levels of law enforcement and the provision of park infrastructure (Leverington *et al*., 2010). For example, there is good evidence that increases in ranger patrols and on-the-ground protection efforts can greatly reduce threats such as logging, fires and hunting (Laurance *et al*., 2012; Tranquilli *et al*., 2014) within PAs. However, there are often further intricacies associated with these parameters: in this case, the success of such law enforcement can be affected by various qualitative factors, including the amount of training provided to park rangers and their individual motivation (Jachmann, 2008). Despite the complexities involved (Jachmann, 2008) and suggestions that even under-resourced PAs can sometimes provide conservation benefits (Blackman *et al*., 2015), it seems fair to conclude that appropriate funding and resource allocation are positively correlated with PA effectiveness (Leverington *et al*., 2010; Laurance *et al*., 2012; Tranquilli *et al*., 2014; Watson *et al*., 2014; Blackman *et al*., 2015), and thus their potential to reduce deforestation and degradation.

Conversely, size is a far more straightforward characteristic of PAs to comprehend, but this has not prevented debate as to how it might affect their performance. Though some suggest that little relationship exists between PA size and effectiveness (Bruner *et al*., 2001), more recent investigations argue that larger PAs experience significantly lower levels of relative forest loss within their borders – for example, in Bowker *et al*. (2017)'s study of PAs in humid African forests, forest loss inside PA boundaries significantly decreased ($p<0.05$) as size increased. Indeed, larger PAs are bordered by large areas of land which, though not officially protected, can effectively buffer against encroachment of adverse activities into the PAs themselves (Blackman *et al*., 2015). However, this is likely an overly-simplified explanation; the common perception that size is linked to success means that larger PAs will often receive greater attention and funding from authorities and non-governmental organisations (NGOs), while it would also be naïve to assume that it does not interact with other factors determining effectiveness (Struhsaker *et al*., 2005; Joppa *et al*., 2008; Blackman *et al*., 2015). For instance, PA performance in the Democratic Republic of Congo improves with size, though their situation in generally inaccessible areas cannot be overlooked as a further potential influence (Bowker *et al*., 2017). Additionally, and to complicate matters, increases in size may subsequently increase the chances of PADDD, owing to the higher opportunity costs of larger PAs associated with resource extraction (Symes *et al*., 2016). Therefore, despite being far less nuanced, the ultimate effect of size on tropical PA performance is no less difficult to ascertain, though variations between countries (Bowker *et al*., 2017) and interactions with other recognised factors (Struhsaker *et al*., 2005; Joppa *et al*., 2008; Blackman *et al*., 2015) do appear evident.

Interplay with additional factors is essential when considering the influence of PA age on effectiveness, though again, views are polarised as to the exact nature of this relationship. Regardless of its direction however, it is generally supported that age is strongly related to the resourcing and management a PA receives (Dudley *et al*., 2007; Andrade and Rhodes, 2012; Blackman *et al*., 2015; Bowker *et al*., 2017). On the one hand, there is the assumption that management will improve with age (Dudley *et al*., 2007), owing to enhanced reputation resulting in increased regional, national and global protection interests (Eagles *et al*., 2002); indeed, increasing age has been argued to positively correlate with local community compliance in management efforts (Andrade and Rhodes, 2012). Alternatively, there is the argument that a recently-established PA, especially if situated in a stable country dedicated to conservation, is more likely to receive adequate resources to facilitate good performance (Blackman *et al*., 2015). Evidence to support this can be drawn from several regions across the tropics, including Mexico (Blackman *et al*., 2015) and the humid forests of central Africa, where PAs gazetted in a post-colonial era are deemed to be in a far stronger position to receive support from local communities (Bowker *et al*., 2017). The influence of age on PA performance may therefore be heavily dependent on location, and particularly on its relationship with management and resource provision.

A PA's location can have important implications for its accessibility, widely regarded as a crucial determinant of effectiveness (Joppa and Pfaff, 2009; Nelson and Chomitz, 2011; Freitas *et al*., 2013; Nolte *et al*., 2013; Pfaff *et al*., 2014; Bowker *et al*., 2017). This can often be considered as a measure of PA 'remoteness', and thus how easily it can be reached by actors intending to undertake detrimental activities, such as logging, mining and hunting (Joppa and Pfaff, 2009). However, because there is no universally accepted definition of 'accessibility', different studies will incorporate various combinations of environmental variables which are perceived to influence it (Joppa and Pfaff, 2009; Nelson and Chomitz, 2011; Freitas *et al*., 2013; Bowker *et al*., 2017), thereby advocating a degree of caution when comparing the findings of such investigations. For example, Joppa and Pfaff (2009)'s meta-analysis focuses on elevation, slope, distance to urban areas and road networks, agricultural suitability and ecoregion; Nelson and Chomitz (2011) also broadly measure accessibility in relation to these variables, though agricultural suitability is considered purely as a function of precipitation estimates, and travel time to major cities and country of origin are included as additional variables. Despite this variation, it is consistently concluded that less accessible PAs are less likely to experience deforestation and degradation (Joppa and Pfaff, 2009; Nelson and Chomitz, 2011; Freitas *et al*., 2013; Bowker *et al*., 2017), and that PA effectiveness is often heavily reliant on location. Therefore, although high-performing PAs may be subject to strict management regimes (Nolte *et al*., 2013) and receive substantial resources (Watson *et al*., 2014), their situation in topographically inaccessible areas, with low surrounding population densities and low agricultural suitability (Joppa and Pfaff, 2009), may ultimately explain their effectiveness.

1.2.5 <u>Tropical Protected Areas – spatial bias in current knowledge</u>

When the issues of tropical deforestation and degradation are considered, research frequently focuses on the humid evergreen forests of Amazonia, Central Africa and Southeast Asia (Laurance, 1999; Fearnside, 2005; Malhi *et al*., 2008; Achard *et al*., 2014), owing to their extremely high levels of biodiversity and significance regarding valuable ecosystem services, particularly the storage and sequestration of atmospheric CO_2 (Malhi and Grace, 2000; Pan *et al*., 2011; Baccini *et al*., 2012; Houghton *et al*., 2015; Avitabile *et al*., 2016; Grassi *et al*., 2017; Houghton *et al*., 2018). This focus is reflected in studies of tropical PAs, with the majority of literature concerned with PA performance across the pan-tropics (e.g. Gaveau *et al*., 2009; De Marques and Peres, 2014; Bowker *et al*., 2017). However, it cannot be forgotten that the tropics comprise a variety of biomes and ecosystems, ranging from evergreen forest to hot shrubland, from montane forest to savannah (Prentice *et al*., 1992), and that these can also be severely threatened by adverse anthropogenic activities (O'Higgins, 2007).

Tropical drylands, including dry forest and savannah ecosystems, are often underappreciated for the rich array of flora and fauna they harbour, and vital ecosystem services they provide. Covering approximately 41% of Earth's surface (Sorensen, 2009), they are home to over a quarter of global biodiversity hotspots (Myers *et al*., 2000), supply important goods and services to support local livelihoods (Maestre *et al*., 2012) and act as a low density but significant carbon sink (Dewees *et al*., 2010; Bastin *et al*., 2017; Brandt *et al*., 2018). Recent assessments even suggest that forest cover across drylands is considerably higher than previously thought, increasing estimates of global forest cover by at least 9%, with important implications for global carbon storage (Bastin *et al*., 2017). However, these ecosystems face severe pressure from both climatic variability and anthropogenic-induced LULCC (Rudel, 2013); carbon losses from drying trends in African drylands between 2010 and 2016 exceeded those from humid forests, being 0.05 and 0.02 PgC yr^{-1} respectively (Brandt *et al*., 2018). Despite this, these ecosystems regularly receive far less protection than their humid forest counterparts. For example, the Brazilian Cerrado contains both considerably fewer (Barr *et al*., 2011) and less effective PAs than Amazonia, even though it harbours around 30% of the country's biodiversity and is experiencing much higher rates of deforestation (Francoso *et al*., 2015). Consequently, a real impetus exists for expanding PA networks in drylands around the world, as well as furthering our current understanding of their overall performance (Nacoulma *et al*., 2011; Carranza *et al*., 2014; Francoso *et al*., 2015; Paiva *et al*., 2015; Ament and Cumming, 2016) and the key factors influencing this effectiveness.

1.3 Monitoring Tropical Protected Areas

By monitoring changes in AGB and land-cover within PAs over a period of time, their performance in terms of habitat conservation and carbon storage can be studied relatively effectively (Gross *et al*., 2009; Nagrenda *et al*., 2013; Schmidtlein *et al*., 2014). A variety of approaches are available to do this, and though field-based methods remain a viable option (Chave *et al*., 2005; Chave *et al*., 2014), remote sensing applications are becoming increasingly popular, with rapid technological advancements rendering them more accurate and accessible than ever before (Lu, 2006; Gibbs *et al*., 2007; Le Toan *et al*., 2011;

Saatchi *et al*., 2011; Baccini *et al*., 2012; Nagrenda *et al*., 2013; Schmidtlein *et al*., 2014; Mitchell *et al*., 2017). A broad range of these exist, with each having associated benefits and disadvantages for estimating AGB and land-cover change (Gibbs *et al*., 2007), and thus PA effectiveness (Nagrenda *et al*., 2013; Schmidtlein *et al*., 2014). It is therefore important to establish the relative utility of such approaches for monitoring tropical PA performance.

1.3.1 Field-based Methods

One approach to estimating tropical ecosystem AGB is to combine long-term forest inventory data with allometric equations (Brown, 1997; Chave *et al*., 2005; Chave *et al*., 2014). These equations are regression models which determine AGB per tree from a combination of tree dimensions (Brown, 1997), including parameters such as diameter-at-breast-height (DBH), wood density and tree height (Chave *et al*., 2005; Chave *et al*., 2014). These are then applied to forest inventory data collected from periodic measurements of permanent sample plots, enabling changes in AGB and carbon density for different ecosystems to be estimated from the unique regression equations associated with them (Brown, 1997; FAO, 2011; Chave *et al*., 2005; Chave *et al*., 2014). More general models can be applied to a wider variety of ecosystems, but will produce less accurate results (Mitchard *et al*., 2009), while locally-based models will produce more accurate estimates, but only of specific areas (Ryan *et al*., 2012).

Though they remain important in assessments of tropical AGB and carbon density, various limitations with such field-based methods must be acknowledged. A constant issue when developing allometric equations is the need to destructively harvest trees to obtain the necessary data; the enormous variety of tree species and sizes in tropical ecosystems means that many trees will require harvesting, an expensive and time-consuming process (Chave *et al*. 2005, Chave *et al*., 2014). However, such samples are often far too small and contain a disproportionally small number of large-diameter trees, rendering them somewhat unrepresentative of the forest at large (Chave *et al*., 2005) and meaning that two models constructed for the same area of forest can yield very different AGB estimates (Brown, 1997; Houghton *et al*., 2001). Additionally, shortcomings may exist with the forest inventory data applied to these allometric equations. Tree height data are important for reducing bias in AGB estimates (Chave *et al*., 2014); for example, incorporating height measurements from 327 tropical forest plots into models reduces estimates of tropical carbon storage by 13% (Feldpausch *et al*., 2012). However, difficulties in measuring this accurately – particularly for closed-canopy forests – can lead to it being neglected in forest inventories (Hunter *et al*., 2013; Larjavaara and Muller-Landau, 2013). Indeed, the laboriousness of compiling these inventories means that inaccuracies stemming from human error and antiquated data are also common (Grainger, 2008), with the limitation of collecting data from relatively small, established, accessible plots preventing truly accurate estimation of AGB across large areas. The presence of such errors therefore advocates caution when employing these approaches to estimate ecosystem AGB change over time, and thus in monitoring PA effectiveness.

1.3.2 Remote Sensing Methods

The abundance of remote sensing data available from both aircraft and satellites presents an extensive and powerful means of monitoring AGB and land-cover change (Lu, 2006; DeFries *et al*., 2007; Gibbs *et al*. 2007; Saatchi *et al*., 2011; Baccini *et al*., 2012; Avitabile *et al*., 2016), and thus the efficacy of tropical PAs for preventing deforestation and degradation within their borders (Nagrenda *et al*., 2013; Schmidtlein *et al*., 2014). Of all available remote sensing applications, those offering the greatest potential for monitoring PA effectiveness are datasets derived from optical sensors, synthetic aperture radar (SAR) sensors, and light detection and ranging (LIDAR) sensors (Gibbs *et al*., 2007; Nagrenda *et al*., 2013; Mitchell *et al*., 2017). Repeated observations over time allow for estimations of changes in forest structure, AGB and carbon stocks, due to both deforestation and the subtler processes of degradation and regrowth (Mitchard *et al*., 2017).

Optical remote sensing data formed the principal means of monitoring habitat changes over larger scales for many decades; this was originally limited to coarse imagery from aerial photography and primitive satellites, but now such data are readily available from a variety of sources and at increasingly fine resolutions (Lu, 2006; Gibbs *et al*., 2007, Nagrenda *et al*., 2013; Mitchell *et al*., 2017). Although very high resolution aerial photography and 3D imagery to <5m can provide detailed information on forest structure and fine-scale degradation (Nagrenda *et al*., 2013), this is only effective over relatively small areas (up to around 10,000 ha; Gibbs *et al*., 2007), is expensive, and allometric model development can be complicated by object shadowing (Lu, 2006; Nagrenda *et al*., 2013). On the other hand, satellite data can provide globally consistent records of land-cover change spanning over thirty years, and though initially coarse, are becoming progressively more sophisticated and available to researchers and policy-makers (Gibbs *et al*., 2007; Nagrenda *et al*., 2013). Lower resolution data (>100m) from sensors such as the Moderate Resolution Imaging Spectroradiometer (MODIS) can be useful for long-term records and real-time monitoring of deforestation in tropical regions (Nagrenda *et al*., 2013), while that at medium resolutions (10-100m), from sensors such as Landsat, offers an archive of land-use history and AGB change from more discreet processes at both local and regional scales (Lu, 2006; Nagrenda *et al*., 2013; Mitchell *et al*., 2017). While medium resolution satellite data can effectively document land-cover changes (e.g. Hansen *et al*. (2013) analysed Landsat data to produce maps of 21st century global forest cover change), AGB stock estimates are produced by correlating ground-based measurements with spectral indices derived from visible and infrared wavelengths (Gibbs *et al*., 2007), a method which yields large uncertainties (Thenkabail *et al*., 2004). Therefore, optical remote sensing data may be considered most useful for tracking changes in land-cover and habitat extent within PAs, with other approaches likely more able to provide accurate estimates of AGB and C stock change over time.

Active remote sensors, including LIDAR and SAR, can offer complementary information to their optical counterparts in studies of forest and AGB change (Strittholt and Steininger, 2007). They are able to provide detailed information on ecosystem structure and biomass (Koch, 2010) in all weather conditions, a significant advantage over optical sensors, where data collection can be hindered by high cloud cover, smoke and haze, and low light levels (Lu, 2006; Mitchard *et al*., 2011; Nagrenda *et al*., 2013). LIDAR systems emit laser pulses which interact with forest canopies and ground surfaces, returning a temporallydistorted energy profile which can be used to determine the height and vertical structure of these ecosystems (Patenaude *et al*., 2004; Gibbs *et al*., 2007; Mallet and Bretar, 2009). Subsequently, AGB levels and carbon stocks may be estimated by applying allometric height-carbon relationship models to these data (Hese *et al*., 2005). Indeed, numerous studies have advocated the utility of LIDAR for investigating AGB and carbon stock changes in tropical ecosystems, particularly when employed in conjunction with other approaches (Saatchi *et al*., 2011; Baccini *et al*., 2012; Harris *et al*., 2012). For example, Saatchi *et al*. (2011) combine ground-based LIDAR and MODIS data to estimate carbon storage across 25 billion hectares of tropical forest. Although penetrative LIDAR sensors demonstrate much promise for obtaining data on tropical AGB change, certain limitations remain: if airborne LIDAR sensors are employed, significant uncertainties are associated with upscaling measurements for AGB and carbon stock estimation (Mitchell *et al*., 2017), while the requirement for supplementary field data will always be a hindrance (Asner *et al*., 2012a). However, the latter could be addressed by use of a ‘universal’ LIDAR model for tropical forest ecosystems, an approach which would enable fast and inexpensive calibration

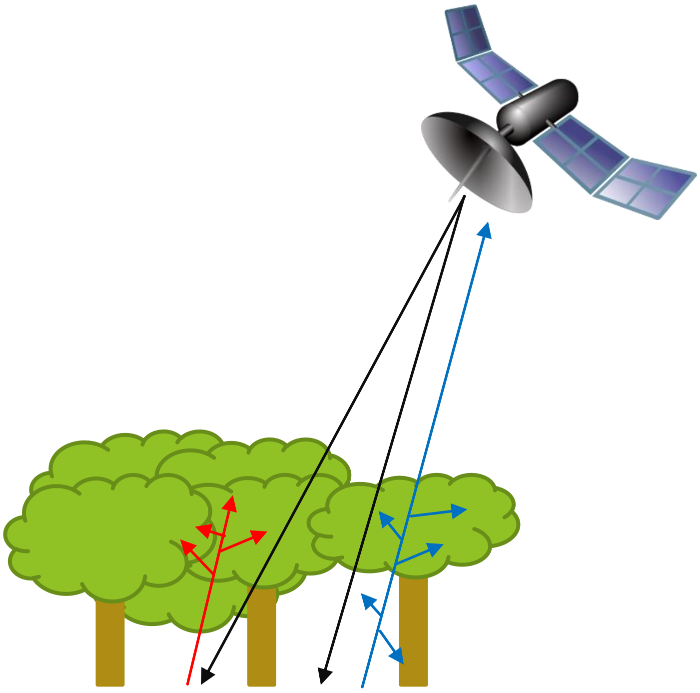


Fig. 1.2: RCS Signal Saturation in High Biomass Environments. The black arrows represent L-band radar waves transmitted from a sensor aboard a satellite: in the lower AGB environment (right), waves (in blue) pass through the vegetation canopy and return to the sensor, whereas in the higher AGB environment (left), waves (in red) cannot penetrate the canopy, and so do not return to the sensor.

of LIDAR data (Asner *et al*., 2012b). This would greatly increase its applicability for estimating AGB and carbon stock changes over large scales, and thus its potential for monitoring PA effectiveness.

In operational terms, SAR sensors are very similar to LIDAR. However, rather than lasers, radar utilises the microwave region of the electromagnetic spectrum, transmitting pulses of polarised electromagnetic waves which interact with ecosystem components before returning to the sensor (Balzter, 2001). The proportion of energy returning to the sensor – the normalised radar cross section (RCS), or 'backscatter' – corresponds to the AGB level of a specific area, with higher AGB levels resulting in more energy returning and thus a higher RCS value (Le Toan *et al*., 1992; Mitchard *et al*., 2009; Ryan *et al*., 2012. However, the AGB density of an area will dictate the effectiveness of different SAR sensors for estimating vegetation biomass. Waves are transmitted between frequencies of 1 – 90 GHz and grouped into different 'bands' according to the equipment required to generate and detect them (Woodhouse, 2006): shorter wavelengths – X-band and C-band – interact with leaves, twigs and small branches (Rauste *et al*., 1994; Le Toan *et al*., 2001; Englhart *et al*., 2011), so there is often little correlation between these RCS values and total area AGB (Le Toan *et al*., 1992). Conversely, longer SAR wavelengths – L-band and P-band – are able to penetrate through forest canopies and interact with major parameters, such as large branches and stems, rendering them far more effective for AGB estimations (Mitchard *et al*., 2009; Ryan *et al*., 2012). In addition to these different bands, SAR data may also be collected at different polarisations. Horizontal-send, horizontal receive (HH) and horizontal-send, vertical receive (HV) are most commonly employed for studies of AGB change, and though both demonstrate a relationship with AGB, cross-polarised HV data responds more strongly to complex forest parameters which change the polarisation of incoming electromagnetic radiation, while parameters which do not change this polarisation, such as soil moisture, will not be detected (Ranson *et al*., 1994; Mitchard *et al*., 2011). Longer wavelength, cross-polarised SAR data, therefore elicits considerable potential for monitoring AGB change within PAs.

L-band SAR has been employed on numerous occasions to estimate AGB and AGB change across tropical ecosystems, both singularly (Mitchard *et al*., 2009;

Lucas *et al*., 2010; Mitchard *et al*., 2011; Ryan *et al*., 2012; Mermoz *et al*., 2014) and in conjunction with other remote sensing methods (Mitchard *et al*., 2012; Collins *et al*., 2015). When used alone, strong relationships have been reported between L-band RCS values and field-based AGB values for tropical dry forest and savannah ecosystems; for example, Mitchard *et al*. (2011) observe a relationship between L-band HV and AGB of $R^2 = 0.86$ in a Cameroonian forest-savannah region. This suggests that AGB changes can be confidently inferred from changes in RCS values, though potential disruptions to this relationship in mountainous environments due to topographic interference (Ghasemi *et al*., 2011; Mitchard *et al*., 2012) must be considered. Furthermore, although a limitation of many remote sensing approaches is their inability to detect subtle changes in tropical ecosystem vegetation (Mitchell *et al*., 2017), L-band SAR can successfully identify small-scale degradation and regrowth across large areas (Mitchard *et al*., 2011; Ryan *et al*., 2012). However, it is arguably ineffective for estimating AGB changes in high biomass, humid forests, as competition for scattering and absorption of the microwave radiation as it passes through the dense canopy causes saturation of the RCS signal (Mitchard *et al*., 2009; *Fig. 1.2*). The approximate threshold at which this occurs varies between studies (Lucas *et al*., 2000; Santos *et al*., 2002; Mitchard *et al*., 2009; Carreiras *et al*., 2017), though it is typically around 100 Mg ha^{-1}, above which greatly reduced sensitivity and negative correlations between RCS and forest biomass have been reported (Mermoz *et al*., 2015). Though this limits the independent use of L-band SAR to lower biomass tropical ecosystems, such as dry forests and savannahs, a fusion approach combining L-band radar with LIDAR data may overcome this issue, as the latter does not suffer from signal saturation (Mitchard *et al*., 2012; Collins *et al*., 2015). Therefore, L-band SAR data alone presents an effective mechanism for monitoring AGB change within PAs in dry forest and savannah ecosystems, while integration with LIDAR is necessary to investigate those in dense, humid forests.

The majority of L-band SAR data available for tropical ecosystems originates from the Japanese Aerospace Exploration Agency (JAXA), collected by SAR sensors aboard the Advanced Land Observing Satellites (ALOS) 1 and 2 (JAXA, 2018). These data have been invaluable to many studies investigating AGB change in tropical dryland ecosystems (Mitchard *et al*., 2009; Mitchard *et* *al*., 2011; Ryan *et al*., 2012), but a major constraint has been the need to collect supplementary field data before the first, and after the last, radar scenes have been taken (Hill *et al*., in prep). After collecting data on vegetation characteristics, allometric models are developed to allow prediction of AGB from L-band RCS values (Mitchard *et al*., 2011; Hill *et al*., in prep). Although a strong relationship between field-derived AGB and RCS values is often observed

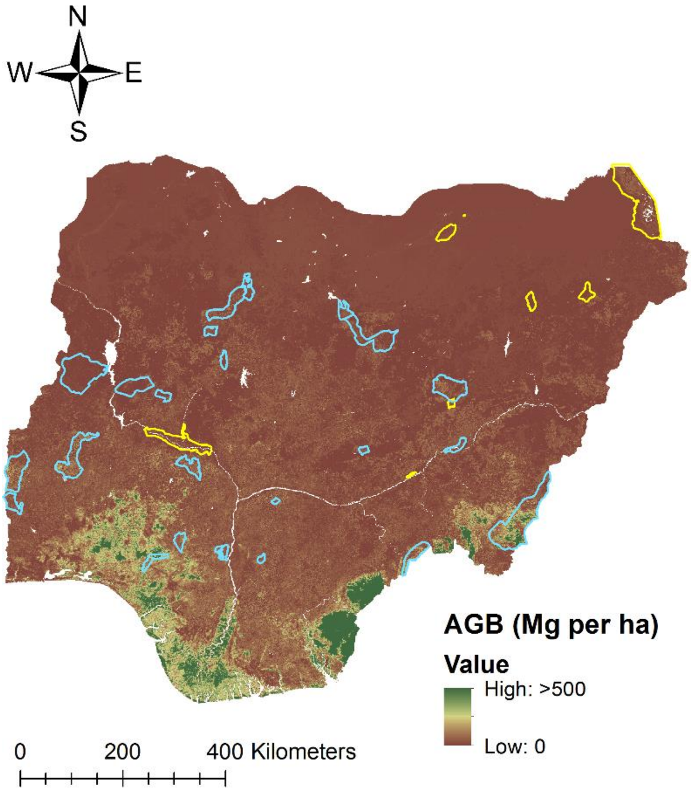


Fig. 1.3: AGB Map of Nigeria. This has been derived from Avitabile *et al*. (2016)'s pan-tropical biomass map, with the locations of the PAs used to obtain this study's RCS-AGB relationship outlined in blue and yellow. Those in blue would be included in the analyses for research questions 2 and 3, while those in yellow would not.

(Mitchard *et al*., 2011), these regression models are unique to particular study areas, so applying them to other regions of potential interest is problematic. As a result, this has generally limited AGB and AGB change estimates to small, pre-meditated investigations, preventing changes in more remote and large-scale areas from being documented (Hill et al., in prep). In order that the L-band SAR data from the ALOS missions may be utilised in AGB change studies to its full potential, alternative approaches will be needed to develop RCS-AGB relationships that are applicable over wider areas.

In order that L-band SAR data may be more effectively employed to monitor AGB changes in tropical PAs, methods that circumvent the requirement for supplementary field data are needed. One means of achieving this is to obtain ‘universal’ RCS-AGB relationships from remote sensing data of tropical AGB (e.g. Avitabile *et al*. (2016); *Fig. 1.3*), which can then be applied to a large number of areas within a particular region. A recently-developed, iterative approach called ‘Biomass Matching’ may provide a solution to the current problem (Hill *et al*., in prep). With this, predetermined regression parameters (i.e. a ‘universal’ RCS-AGB relationship) can be used to estimate AGB change within PAs over time from relevant L-band SAR data. This could render studies of PAs in dry forest and savannah regions considerably more time- and cost-effective, allowing assessments of PA performance to be undertaken far more easily.

1.4 Nigeria – deforestation, degradation and protected areas

Forest resources are essential to many developing nations in the tropics, though it is often these countries where forests and natural ecosystems face the greatest pressures. Nigeria is no exception to this rule: forest commodities account for roughly 2.5% of its GDP, directly provide employment for over 2 million people (UNDP, 2016), and are the primary building material and fuel resource for much of its population (Oriola, 2009). Simultaneously, the country has one of the highest rates of forest loss in the world, with its total forest cover decreasing from approximately 17,324,000 ha in 1990 to 9,041,000 ha in 2010, a loss of 52.2% (FAO, 2010). This decline has been driven by a multitude of factors, including agricultural expansion, logging, mining and fuelwood extraction; as the country’s population continues to rapidly increase, pressures from these activities are unlikely to lessen (Ogunwusi, 2013). Such alarming rates of forest clearance and degradation present serious issues for biodiversity and ecosystem services. Most crucially, this may be responsible for up to 87% of the country’s CO_2 emissions (Balarabe, 2011; UNDP, 2016). Consequently, for Nigeria to meet its NDCs in the context of the Paris Climate Agreement (Grassi *et al*., 2017), significant reductions in deforestation and habitat degradation within its borders will be required.

Although clearance and degradation of the mangroves and dense, humid forests of southern Nigeria clearly represent a serious problem, the importance of the dry forests and savannah vegetation which cover three quarters of the country's area cannot be underestimated (Oriola, 2009). These areas are a low density but significant carbon store (Dewees *et al*., 2010; Bastin *et al*., 2017; Brandt *et al*., 2018), averaging 30 Mg C ha^{-1} in AGB (Alamu and Agbeja, 2011), and are home to many endemic tree species of great social and cultural significance (CITES, 2015). As these ecosystems come under increasing pressure from agricultural expansion, and unsustainable logging and fuelwood extraction (Blackett and Gardette, 2008; Wessels *et al*., 2013), PAs will be integral to conserving important habitats and in efforts to stem the rampant deforestation and degradation afflicting much of the country. However, thus far, Nigerian PAs have been the subject of very little research, and those within the country's extensive dryland zone have received minimal attention from the academic community. Furthering our understanding of how effective such PAs are for safeguarding habitats, and the factors which influence their performance, could be extremely important in the context of conservation and for Nigeria to honour its commitments to the Paris Climate Agreement.

1.5 Project Rationale

PAs across the tropics have enormous potential to conserve and enhance floral and faunal diversity and valuable ecosystem services, contributing to international biodiversity and climate change targets (Juffe-Bignoli *et al*., 2014). Until now, research into their performance has primarily focused on those situated in dense, humid forests (Struhsaker *et al*., 2005; Jachmann, 2008; Gaveau *et al*., 2009; Scharlemann *et al*., 2010; Nelson and Chomitz, 2011; Laurance *et al*., 2012; Pfeifer *et al*., 2012; Soares-Filho *et al*., 2014; Bowker *et al*., 2017) often at the expense of those in drylands, despite the importance of these ecosystem in terms of biodiversity and global carbon cycling (Carranza *et al*., 2014; Francoso *et al*., 2015; Paiva *et al*., 2015; Bastin *et al*., 2017; Brandt *et al*., 2018). L-band SAR presents an effective means of estimating AGB and AGB change across dry forests and savannahs (Mitchard *et al*., 2009; Lucas *et al*., 2010; Mitchard *et al*., 2011; Ryan *et al*., 2012; Mermoz *et al*., 2014), and may thus be particularly appropriate for monitoring AGB change within tropical dryland PAs, furthering our understanding of their performance in relation to similar unprotected lands, and determining the most important factors influencing their ability to prevent deforestation and degradation. Though the need for supplementary field data has previously restricted habitat monitoring with L-band radar to pre-meditated and relatively small-scale studies (e.g. Ryan *et al*., 2012), novel approaches may be able to circumvent this limitation, allowing assessments of AGB change over much larger areas, in far less time and at a fraction of the cost (Hill *et al*., in prep). If this method is robust, L-band SAR could be employed to monitor PA performance across tropical drylands, providing vital information for policy-makers at regional, national and international levels.

1.6 Aims and Research Questions

1.6.1 Aims

The principal aims of this investigation are therefore as follows:

- To test the efficacy of 'Biomass Matching' for estimating AGB change within tropical dryland PAs over a certain period of time, whereby changes in AGB will act as a proxy for PA effectiveness.
- To quantify AGB change in PAs, evaluating their effectiveness and the factors influencing their performance.

1.6.2 Research Questions

The aforementioned aims will be addressed through the following research questions:

1) *How effective is Biomass Matching for detecting and estimating aboveground biomass change in dry forests and savannahs?*

This will determine whether Biomass Matching can detect both large-scale and subtle AGB changes in these ecosystems, and how accurate change estimates are when compared to approaches using supplementary field data.

2) *How effective are protected areas for aboveground biomass conservation (compared to non-protected areas)?*

Here, AGB change in PAs will be quantified and compared to that in similar unprotected areas, testing whether PAs are an effective means of habitat conservation.

3) *What are the main factors influencing protected area effectiveness?*

This will assess whether PA performance can be explained by a number of quantifiable factors, determining how important these are individually, as well as the significance of interrelations between them.

Additionally, the utility of Biomass Matching will be further scrutinised by a case study, which will use the approach to assess the performance of a particularly reputable PA in Nigeria:

4) *Habitat disturbance in Taraba State, Nigeria – can Biomass Matching verify woodland clearance, and to what extent can protected areas offer a solution to the problem?*

Methodology

2.1 Methods Summary

This study focuses on 21 PAs situated in the dry forests and savannahs of Nigeria, ecosystems which comprise over 75% of the country's land area (Omofonmwan and Osa-Edoh, 2008; Oriola, 2009). PAs ranged in size from 11,733 ha to 608,410 ha, and were downloaded from the World Database on Protected Areas (WDPA). To estimate AGB change 2007-2017 in these PAs, a 'universal' RCS-AGB relationship – developed by regressing RCS data against AGB data (derived from Avitabile *et al*. (2016)) for each PA – was applied to L-band SAR data collected by JAXA's ALOS 1 and 2 satellites; this was subsequently subjected to the novel Biomass Matching approach (Hill *et al*., in prep). Steps were taken to assess the utility of the method for both detecting and estimating AGB change. PA effectiveness was considered as a function of AGB change (Mg ha^{-1}) between 2007 and 2017: a higher AGB per ha in 2017 than 2007 indicated an 'effective' PA, and vice versa. Overall PA effectiveness was determined by comparison to 12 similar, unprotected control areas (CAs), which were created in ArcMap 10.5.1 and subjected to the same process to estimate their AGB change 2007-2017. To determine the influence of different factors (size; age; level of protection; accessibility) on PA effectiveness, appropriate data were collected, and relevant statistical analyses were undertaken.

2.2 Study Area

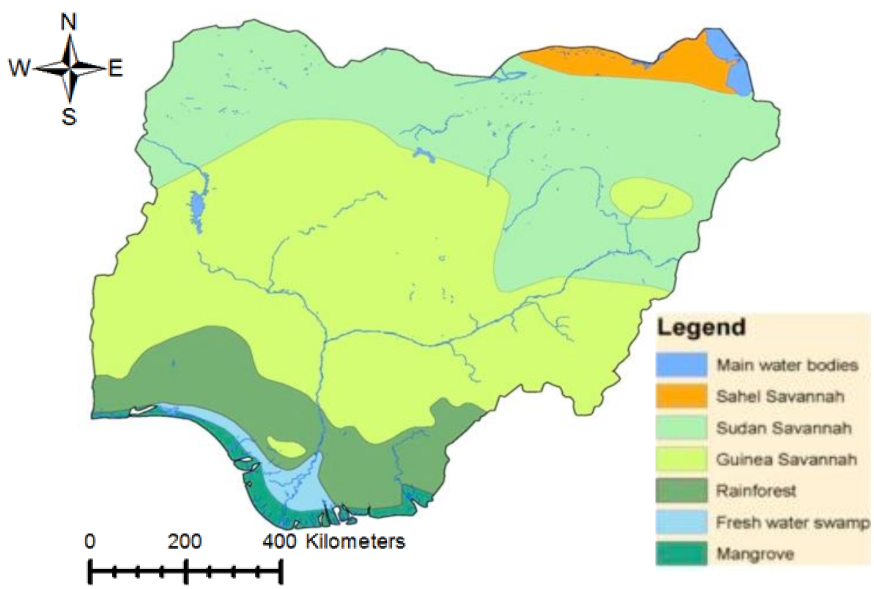


Fig. 2.1: Vegetation Zones of Nigeria. Significant watercourses and water bodies are also displayed (Adapted from: Papaioannou, 2016).

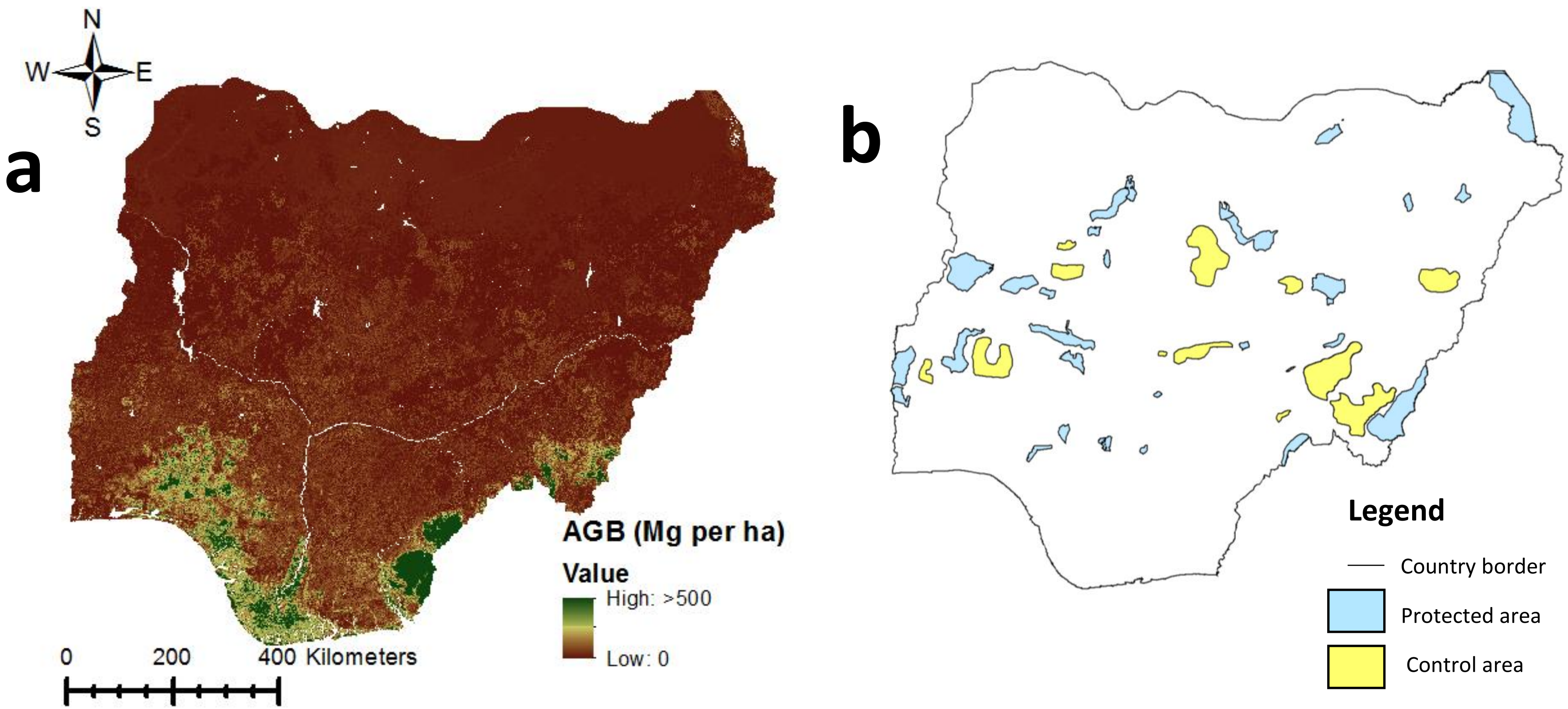


Fig 2.2: a) AGB (Mg ha^{-1}) Across Nigeria. This was derived from the pan-tropical AGB map of Avitabile *et al*. (2016). The highest densities are found in the mangroves and dense forests of the far south, with levels becoming progressively lower into the northern parts of the country. b) PA Locations. The locations of the original 30 PAs, and the 12 CAs, to be included in the analysis. CAs were created to avoid overlap with any PAs listed in the WDPA, the majority of which are not displayed.

Nigeria is situated in West Africa at the inner corner of the Gulf of Guinea, encompassing latitudes 3º15’ - 13º30‘N, and longitudes 2º59’ - 15º00’E (Federal Republic of Nigeria, 2017). Home to over 190 million people, it is already the most populous country on the continent, and with a growth rate of 2.7% per annum, its population is predicted to eclipse that of the United States by 2050 (UN, 2017a,; 2017b). Rapid urbanisation in recent decades (Omofonmwan and Osa-Edoh, 2008) has led to 48% of the country’s population living in towns and cities (UN, 2017a). However, a weak economy and poor energy infrastructure means that most urban dwellers, as well as those in rural areas, still rely on fuelwood for much of their energy (Gutti *et al*., 2012). Indeed, in some parts of Nigeria, over 95% of households depend on biomass as their primary energy source (UNDP, 2016); this has placed considerable pressure on the country’s forest resources. Supplement this with agricultural expansion, mining and petroleum exploration, and unsustainable logging (Blackett and Gardette, 2008; Gutti *et al*., 2012; Ogunwusi, 2013; Wessels *et al*., 2013), and it is clear that forests and woodlands across Nigeria are becomingly increasingly vulnerable to clearance and degradation, including those within PAs.

Climate strongly influences how different vegetation types are distributed across Nigeria, which subsequently determines the average AGB density of natural vegetation in different regions. The country covers almost all climatic belts of West Africa (Abiodun *et al*., 2013), with a strong north-south rainfall gradient (Federal Republic of Nigeria, 2017): over 2000mm of rain falls on the humid, southern reaches each year, while the semi-arid north can receive less than 600mm annually (Abiodun *et al*., 2013). Consequently, conditions in the south are ideal for mangroves along the coast and dense, humid forests inland (Abiodun *et al*., 2013; Federal Republic of Nigeria, 2017). Guinea and Sudan savannah regions include the dry forests, woodlands and savannah comprising the country’s central belt, before giving way to marginal Sahel savannah in the extreme north (*Fig 2.1*; Abiodun *et al*., 2013; Federal Republic of Nigeria, 2017). Mangroves and dense tropical forests are by far the highest AGB density ecosystems: Nigeria has the most extensive mangrove forests in Africa (Ndukwu and Edwin-Nwosu, 2007) which can hold up to 870 Mg ha^{-1} of live biomass (Donato *et al*., 2011), while intact humid African forests have mean AGB densities of 360 Mg ha^{-1} (Avitabile *et al*., 2016). Although dry forest and savannah regions have far lower AGB levels – usually around 60 Mg ha^{-1} (Alamu and Agbeja, 2011) – the extent of these ecosystems in Nigeria renders them significant carbon stores (*Fig 2.1; Fig 2.2a*). Therefore, as so much of Nigeria's primary forest loss is now taking place in these savannah regions (Wessels *et al*., 2013; CITES, 2015; Ahmed *et al*., 2016), it is crucial to further our understanding of practices which may help to mitigate this.

2.3 Selection of Protected Areas

To investigate PA performance in Nigeria's extensive savannah regions, data were obtained from the World Database on Protected Areas (WDPA). This is a comprehensive resource, providing a wealth of material on PAs across the globe, including 'Reported Area', 'Status Year' and 'IUCN Management Category', as well as shapefiles delimiting their position and spatial extent. Though over 1000 PAs are reported to exist within Nigeria, many of these are afforded only the most basic information, rendering them insufficient for focused investigations. Consequently, an original subset of 30 PAs broadly situated within the country's central savannah belt (*Fig. 2.2*b) were selected for analysis, with the relevant shapefiles downloaded freely from the WDPA (available at: https://protectedplanet.net/country/NG); these would be essential for all aspects of the investigation. This would however, eventually be reduced to 22, due to issues with a number of the PAs upon input to the Biomass Matching process. In relation to research question 2, an additional sample of CAs would be required to compare PAs and unprotected areas in terms of effectiveness: unlike a number of similar studies, which employ 'matching approaches' to randomly generate CAs (Andam *et al*., 2008; Gaveau *et al*., 2009; Joppa and Pfaff, 2010; Nelson and Chomitz, 2011; Carranza *et al*., 2014; Blackman *et al*., 2015; Bowker *et al*., 2017), this investigation subjectively created CAs in ArcMap 10.5.1. Care was taken to ensure that these did not overlap with any reported existing PAs by the WDPA.

2.4 ALOS and ALOS 2

To develop a 'universal' RCS-AGB relationship, and to estimate AGB change 2007-2017 in all PAs and CAs, L-band radar data were downloaded from JAXA (available at: http://www.eorc.jaxa.jp/ALOS/en/palsar_fnf/data/index.htm). These data were collected by the ALOS 1 (2007-2010) and 2 (2015-) satellites' phased array type L-band synthetic aperture radars (PALSAR 1 and 2). The first mission (ALOS 1) aimed to implement the first fine and medium spatial resolution global acquisition strategy for satellite sensors, achieving almost gap-free global coverage – around 95%, excluding Antarctica – during its four-and-a-half year operational period (Rosenqvist *et al*., 2014). This was succeeded by the ALOS 2 satellite in 2014, continuing the work of its predecessor with a comprehensive acquisition strategy and enhanced PALSAR instrument (Rosenqvist *et al*., 2014).

For this investigation, data were freely obtained from the global 25m resolution PALSAR-2/PALSAR mosaic, where raw SAR data have been subjected to sophisticated processing and analysis methods to give a 'seamless global SAR image' on an annual basis 2007-2010, and 2015- (JAXA, 2018a). This processing entails various procedures, including calibration of raw images using published coefficients (Shimada and Otaki, 2010), orthorectification and slope correction using the 90m Shuttle Radar Tomography Mission digital elevation model (SRTM DEM; Shimada, 2010) and projection to a geographic coordinate system (Shimada *et al*., 2014); the result is a pre-processed L-band SAR dataset, available in both HH and HV polarisations (JAXA, 2018a). This use of free, pre-processed data to monitor tropical AGB change differs from the approach of previous studies, which process raw data using their own unique procedures (Mitchard *et al*., 2009; Lucas *et al*., 2010; Ryan *et al*., 2012). Nevertheless, JAXA's yearly global mosaics provide an effective means of tracking tropical AGB change over time (Shimada *et al*., 2010).

To monitor AGB change in PAs, appropriate data tiles were downloaded from the PALSAR-2/PALSAR mosaic in HV polarisation for each year – over Nigeria, radar scenes were typically collected by the satellite during the wet season, which usually runs April – October across the country. These tiles were imported into ArcMap 10.5.1 as raster images, where they were combined with the WDPA (and subjectively generated CA) shapefiles so that the areas of PAs (and CAs) could be extracted. As the 25m resolution mosaic data are stored in digital number form, processing was undertaken to convert this to RCS values for each PA for each year. This enabled a RCS-AGB relationship to be developed from the set of PAs; combined with RCS values for each PA for each year, AGB change within PAs 2007-2010 (i.e. 2007, 2008, 2009 and 2010) and 2015-2017 (i.e. 2015, 2016 and 2017) could be estimated (for full details of the process, see Appendix A).

2.5 A 'Universal' RCS-AGB relationship

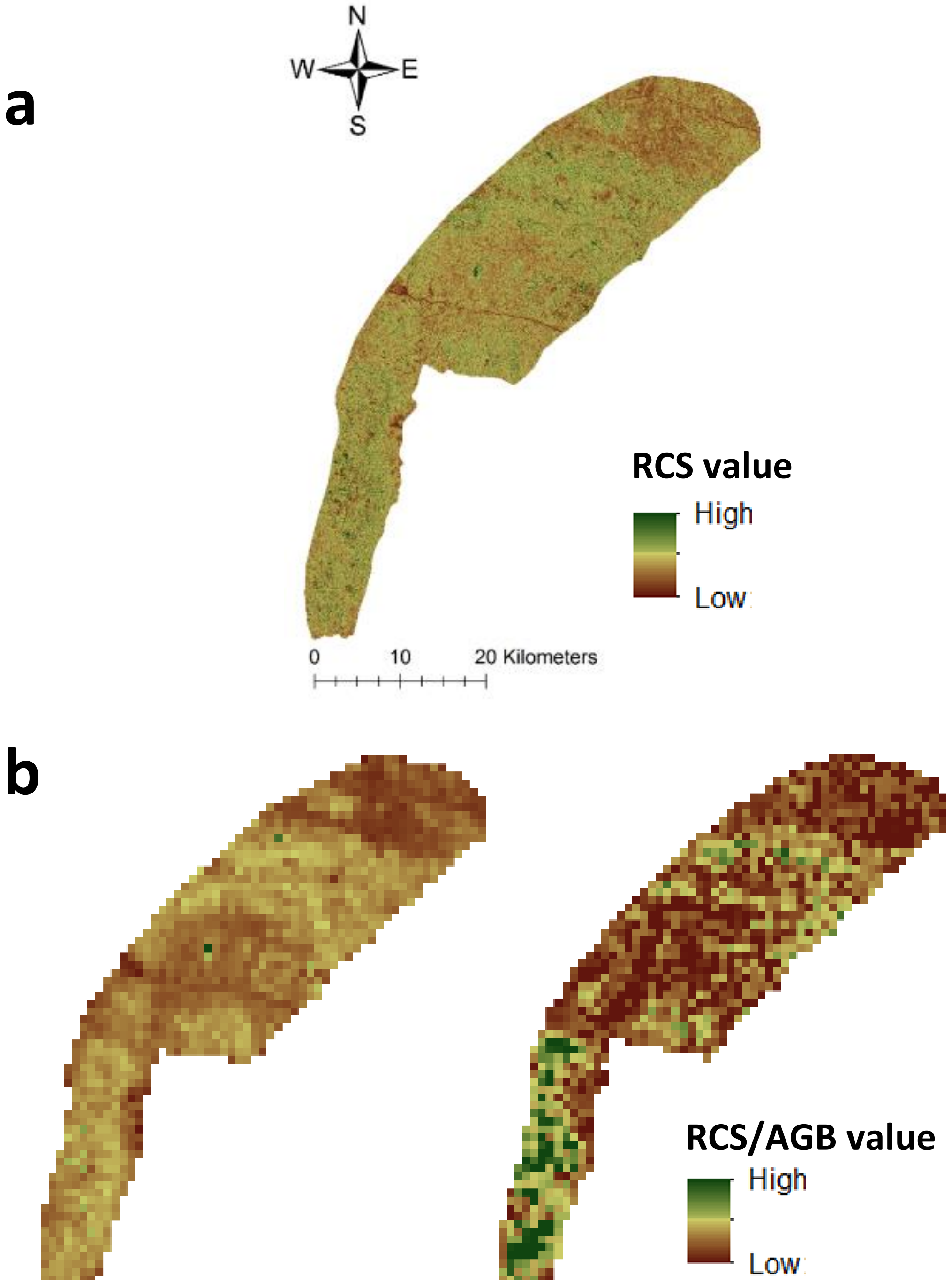


Fig. 2.3: a) RCS Image of Kashimbila at 25m Spatial Resolution, and b) Images of Kashimbila at 1km Spatial Resolution. RCS (left) is compared to an AGB image of the same area (right).

For any study using radar data to predict AGB change, a relationship between the RCS – or 'backscatter' signal – and AGB for a particular area or region must be developed. Usually, this involves regressing RCS values against field-based AGB measurements collected from plots before the first, and after the last, radar scenes are taken (Ryan *et al*., 2012; Hill *et al*., in prep). For example, in Ryan *et al*. (2012)'s study of small-scale AGB change in Mozambican woodlands, they develop a regression equation based on inventory data from 96 permanent forest, woodland and cropland plots situated in the south of their study area. However, rather than using field measurements, this investigation used AGB data derived from the pan-tropical biomass map of Avitabile *et al*. (2016), which combines multiple data sources to produce a fused 1km resolution map of AGB estimates encompassing the years 2000-2010. Therefore, to develop the RCS-AGB relationship, 2010 RCS data for each PA was aggregated from 25m to 1km resolution in ArcMap 10.5.1 so that the two datasets were at the same spatial scale, and RCS and AGB in equivalent pixels could be compared (*Fig. 2.3*). 1km resolution RCS and AGB data for each PA was then compiled in Matlab R2017a and subjected to linear regression analysis to produce a regression model of

$$Y_{AGB} = -25.01 + 1091.80(RCS)$$

with $R^2 = 0.29$ and p-value of 0 ($p<0.001$). This indicated a statistically significant relationship at the 99.9% confidence interval between AGB data from Avitabile *et al*. (2016) and the equivalent 1km RCS pixels processed from 2010 ALOS PALSAR data, though this is unsurprising, as 26,331 observations were included in the model. This pre-existing RCS-AGB relationship would allow AGB for individual pixels to be derived from RCS data for each PA, and therefore the potential to estimate AGB change within these PAs between 2007 and 2017.

2.6 <u>Biomass Matching</u>

In order to detect and estimate AGB change between 2007 and 2017 within both PAs and CAs, the prepared L-band SAR data were subjected to Biomass Matching. Biomass Matching is an optimisation approach to improve the regression parameters of each radar scene being used in AGB change analysis: a generic RCS-AGB relationship (such as that described above) is applied to at least the first radar scene, after which an iterative process can optimise the regression parameters for the remaining scenes under the assumption that AGB in undisturbed pixels will not change (Hill et al., in prep). From this, AGB changes within an area over time can be estimated (Hill et al., in prep). Processed radar scenes were exported from ArcMap 10.5.1 in the '.tif'

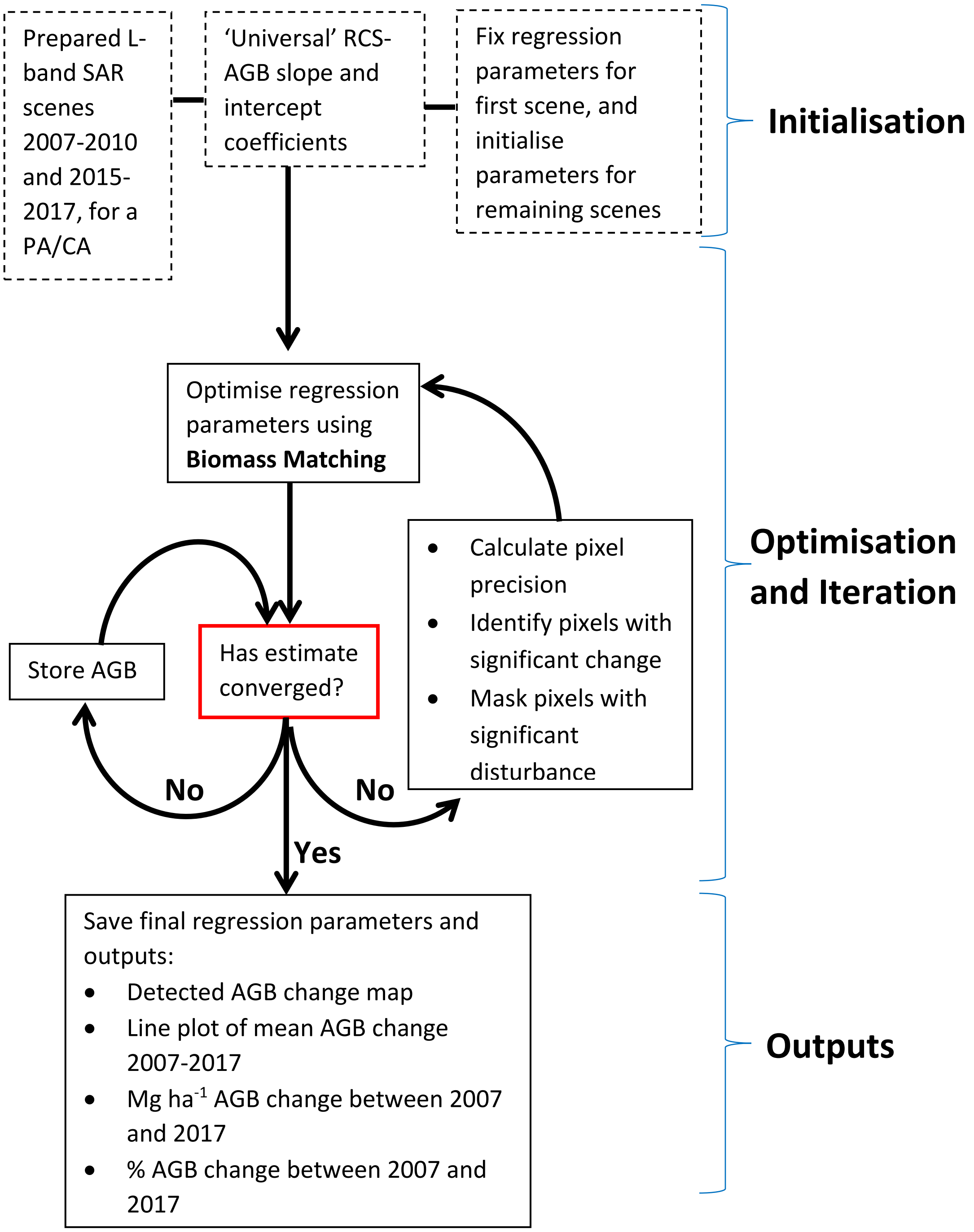


Fig. 2.4: The Biomass Matching Procedure (for an individual PA/CA). The step highlighted in red is not carried out on the first iteration.

file format for each area, and then imported into Matlab R2017a. Here, the universal RCS-AGB relationship and data for each PA (and CA) were inputted to this novel method, giving the following outputs: maps of detected AGB change, plots of mean AGB change 2007-2017, and the estimated total (in Mg ha^{-1}) and percentage changes in AGB between 2007 and 2017 for each area. A summary of the process is presented above (*Fig 2.4*), with a step-by-step account of each stage detailed below:

- **Initialisation**: Prepared L-band SAR data for a PA/CA in the '.tif' format was imported into Matlab R2017a for Biomass Matching; this file was comprised of seven raster images – or radar scenes – corresponding to each year 2007-2010, and 2015-2017. The universal RCS-AGB relationship was applied to the first scene (i.e. the year 2007), defining the slope and y-intercept coefficients which would be used to estimate per-pixel AGB values from the RCS data; the remaining six scenes were also initialised with these coefficients (Hill *et al*., in prep). Before commencing the procedure, the level of subsampling (≥1, where 1 includes all pixels, and higher integers include progressively fewer) and the change difference threshold for the process had to be set. The subsampling level greatly affected the amount of time each iteration of the process would take, so rigorousness was dependent on PA/CA size; for instance, small areas contain relatively few pixels, so the level could be set to '1'. The change difference threshold would determine the number of iterations the process would have to go through before estimates of AGB change between scenes converged and the outputs were produced – this is discussed in greater detail below. After fixing the regression coefficients for the first radar scene, and setting the subsampling level and change difference thresholds, the process could be initiated.
- **Optimisation and Iteration**: The optimisation procedure of Biomass Matching is similar to quantile-quantile (Q-Q) fitting: this is where two probability distributions are compared by plotting their quantiles against one another, with values roughly sitting on a 1:1 line if their distributions are similar (Wilk and Gnanadesikan, 1968). However, Biomass Matching differs in that it uses real values (e.g. AGB of individual pixels for 2007 and 2008 scenes) rather than quantiles, to optimise the regression parameters applied to the following six radar scenes. The procedure gains confidence by matching the AGB of all unique scene-pair

combinations – as there are seven scenes for each PA, this gives 21 possible combinations. The AGB for individual pixels in different scenes is assumed to be identical; any pixels with different AGBs must therefore be masked prior to fitting, or the matching process' attempts to make these scenes identical will remove any real traces of AGB loss or gain which have occurred (Hill *et al*., in prep). By masking these AGB changes, the optimisation procedure minimises the difference of sorted AGB between the seven scenes; the process iterates through enough times until AGB change between all scenes becomes less than the pre-set change difference threshold of either 0.001 or 0.0001%, depending on the PA/CA; some would not meet the lower threshold. After this has occurred (the AGB changes have 'converged'), regression coefficients can be found for areas of constant AGB, which can then be applied to the subsequent six radar scenes to predict per-pixel and overall AGB for each scene. (Hill *et al*., in prep).

- **Outputs**: The products of the Biomass Matching process would be essential for addressing the research questions established in section 1.6. The AGB change maps and line plots of mean AGB Change 2007-2017 for a PA/CA would be needed for validation purposes, testing the ability of the process to both detect and estimate AGB changes within a certain area (research question 1). Meanwhile, statistics of mean per ha and percentage AGB change would be required to answer research questions 2 and 3, determining the effectiveness of the sample of PAs when compared to the CAs, and assessing which factors may be the most important in influencing this effectiveness. Research question 4 would require all outputs to investigate the issue of woodland clearance in Taraba State, Eastern Nigeria, and the potential importance of Gashaka-Gumti National Park for conservation efforts.

2.7 Research Question 1 – Validating the Biomass Matching Approach

Before the Biomass Matching approach could be used for analysis, its ability to detect and estimate AGB change had to be assessed. Two methods were available to determine the former: visual validation and synthetic validation. Visual validation was the less sophisticated approach; here, the AGB change maps produced for each PA were compared to other data sources which might display AGB or land-cover change, such as Google Earth. Alternatively, synthetic validation entailed manipulating the RCS data imported to the Biomass Matching approach in order to simulate AGB loss or gain within a PA. Prior to Biomass Matching, a particular sector of a PA for one of its seven radar scenes was selected, with all RCS values for that sector reduced (or increased) to simulate a certain level of AGB loss (or gain). For example, dividing values by 2 would simulate 50% AGB loss within that particular sector. Following Biomass Matching, an AGB change map of the scene where clearance had been simulated could be obtained and compared to a non-doctored scene, to ascertain whether the process had detected the change.

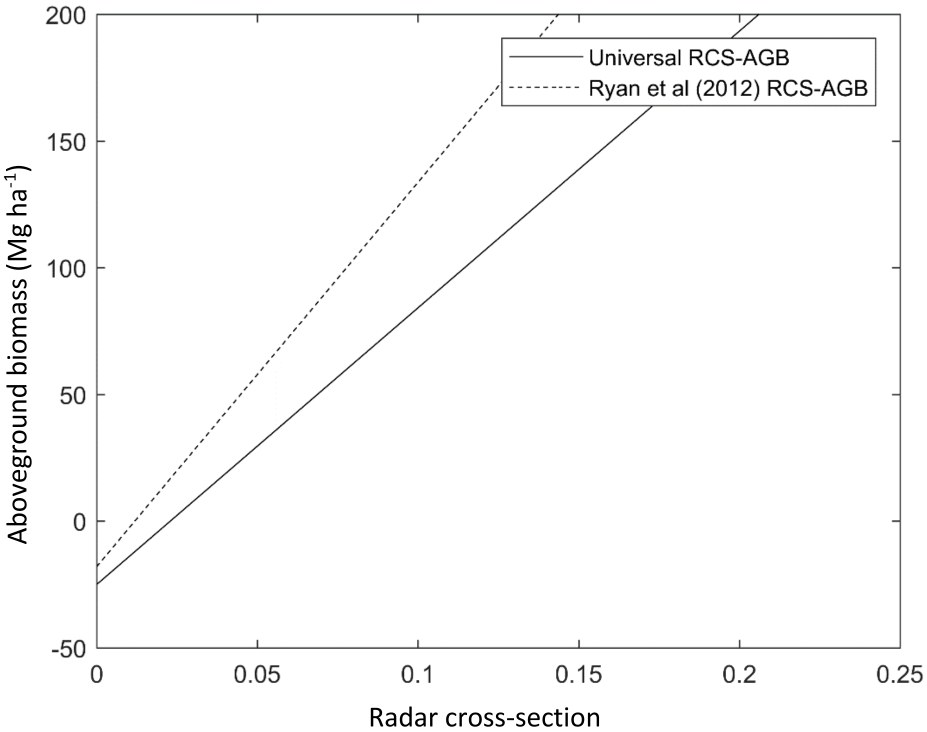


Fig. 2.5: Universal and Ryan *et al*. (2012)'s RCS-AGB relationships. The universal regression has the equation $Y_{AGB} = -25.01 + 1091.80$, while Ryan *et al*. (2012)'s is $Y_{AGB} = -18 + 1517$.

A different method was required to test the robustness of the Biomass Matching approach for estimating AGB change. This is because estimates of AGB change depended not only on the L-band RCS data, but also on the RCS-AGB relationship derived from the Avitabile *et al*. (2016) pan-tropical biomass map; the slope and y-intercept coefficients would directly determine the AGB predicted for a given RCS value. Therefore, the universal RCS-AGB regression of this study was compared to that of Ryan *et al*. (2012), who use field-based AGB measurements to develop a relationship specific to their 116,000ha study area of Mozambican miombo woodland (*Fig. 2.5*). Both regressions were applied to the RCS data for each PA in this study; the per ha and percentage AGB change 2007-2017 predicted by each regression for each PA could subsequently be compared, and potential causes of any differences explored.

2.8 <u>Research Question 2 – Effectiveness of Protected Areas vs Control Areas</u>

While PA performance was treated as a function of AGB change, it was important to determine whether PAs were more (or less) effective for conservation than similar unprotected areas. To address this, AGB change within PAs was compared to that of the CAs, considered in terms of both per ha and percentage AGB change between 2007 and 2017. To create the CAs, the ‘Draw’ tool was used in ArcMap 10.5.1 to construct twelve polygons in unprotected parts of Nigeria’s dry forest and savannah region. Various sources were consulted during this process: the WDPA dataset was used to ensure that these CAs did not overlap with PAs of any kind, and were far enough away from PA borders to avoid the influence of potential positive or negative spillover; the AGB change map provided by the remote sensing application ‘Global Forest Watch’ (available at globalforestwatch.org) guaranteed that only genuine AGB changes Ii.e. due to deforestation, degradation, reforestation or afforestation) would be captured; elevation data from “ALOS World 3D – 30m (AW3D30)” (JAXA, 2018b) prevented CAs from being situated on floodplains, as floodwaters can interfere with the RCS signal to mimic deforestation. The created CAs fell into pre-determined ‘Small’, ‘Medium’, ‘Large’, or ‘Very Large’ size classes. This allowed these areas to be compared with PAs of similar sizes when addressing research question 2. Though arguably more effective than simple inside-outside comparisons, this non-random method of configuring CAs has various limitations when compared with ‘matching’ approaches (see section 1.2.3) – these will be discussed in detail in section 4.2.2.

2.9 Research Question 3 – Factors Influencing Protected Area Effectiveness

Although a great many factors are cited as potential drivers of PA effectiveness, this investigation would include only the most commonly recurring and easily quantifiable in detailed statistical analyses. The factors ultimately selected were PA size, age, level of protection, and accessibility; the data required to assess the influence of each of these on PA effectiveness was derived from various sources.

2.9.1 Size

Information on spatial extent was initially obtained from the WDPA, as this was available for every PA included in the study. However, clear inaccuracies with this (Nagrenda *et al*., 2013), led to size instead being calculated in MATLAB R2017a, and reported in hectares. As a validation method, these calculated spatial extents were compared to ArcMap-derived GIS areas of each PA, which were found to closely align and thus suggested a robust approach.

2.9.2 Age

The year of establishment for most PAs was obtained from the WDPA, though this was unavailable for a small number: Ebbe/Kampe, Kogo and Meko. In these circumstances, age was estimated by reference to unverified internet sources, such as http://www.parks.it/world/NG/Eindex.html; this could present issues at later stages of analysis for research question 3.

2.9.3 Level of Protection

As above, data were available from the WDPA, which provides the ‘English Designation’ (e.g. National Park) for a PA, along with its associated ‘IUCN Management Category’, if applicable. For example, Gashaka-Gumti is a designated National Park, affording it an IUCN category of II. Though an invaluable resource, there were at times issues with duplicate shapefiles being present for a PA, with different designations and IUCN categories reported for each; this, again, could present issues when addressing research question 3.

2.9.4 Accessibility

This was the most complex factor to consider, as a variety of variables are often perceived to influence this (Andam *et al*., 2008; Joppa and Pfaff, 2009; Nelson and Chomitz, 2011; Carranza *et al*., 2014; Bowker *et al*., 2017). For the purposes of this investigation, a small number of those often cited as having the most significant influence on PA accessibility (and thus overall effectiveness) were selected for inclusion:

- *Topography* – this was treated as a function of the mean elevation (in meters above sea level) and slope (in degrees) of each PA. These values were obtained from the freely available digital surface model "ALOS World 3D – 30m (AW3D30)", a global 3D map with approximate horizontal and vertical resolutions of 30m and 5m respectively (JAXA, 2018b). Appropriate data were downloaded and imported into ArcMap 10.5.1, subsequently being processed to give mean elevation and slope values for all PAs and CAs.
- *Proximity to Major Settlements* – following previous studies, such as Bowker *et al*. (2017), 'major' settlements were defined as any with populations of greater than 50,000 people in 2010. Data were obtained from NASA's Socioeconomic Data and Applications Center (SEDAC) in the form of the 'Gridded Population of the World, Version 4 (GPWv4) – Administrative Unit Center Points with Population Estimates, Revision 10' (available at: https://doi.org/10.7927/H46H4FCT). This dataset contains locations – at approximately 1km resolution – and population estimates for city centroids between 2000 and 2020 in five year increments, derived from globally-integrated national population data from the 2010 round of the 'Population and Housing Censuses' (CIESIN, 2017). For Nigeria, 769 city centroids with populations of over 50,000 were provided for 2010; these point shapefiles were imported into ArcMap 10.5.1 for processing, the details of which are discussed below.

- *Proximity to Major Roads* – the 'Global Roads Open Access Data Set, Version 1 (gROADSv1)' from SEDAC combines the best available public domain roads data 1980 – 2010 into a global dataset; though spatial accuracy vastly improves on previous datasets, there can still be considerable variation between countries (CIESIN, 2013). A polyline shapefile containing information on all major roads for Africa was downloaded from http://sedac.ciesin.columbia.edu/data/set/groads-global-roads-open-access-v1, and imported into ArcMap 10.5.1.

When processing major settlement and road data, a different approach was taken to that of previous studies, which often employ Euclidean distance measures to give mean distance from city centroids and roads for protected areas (Nelson and Chomitz, 2011; Bowker et al., 2017). Instead, standardised buffer zones of 15km were generated around each protected area in ArcMap 10.5.1; buffer size was founded on inferences from literature, regarding the distances individuals and households in sub-Saharan Africa might be expected to travel for harvesting of fuelwood and timber (Masozera and Alavalopati, 2004; Hiemstra-van der Hoorst and Hovorka, 2009; Matsika et al., 2013). Proximity to Major Settlements was recorded as the number of city centroids within a PA or CA and its associated buffer, whilst the total length of road (in km) within an area and its buffer was calculated to give a measure of its Proximity to Major Roads.

2.9.5 Statistical analysis

To thoroughly address research questions 2 and 3, analyses to test for both statistically significant difference and statistically significant relationships were undertaken. To determine the effectiveness of PAs in relation to similar unprotected areas (research question 2), independent samples t-tests were employed to test for statistically significant difference in mean per ha AGB change between PAs and CAs as a whole, as well as for differences in AGB change between subsamples (e.g. small PAs vs. small CAs). The unequal number of PAs and CAs overall (n=21 and n=12 respectively) and in the subsamples, prevented the use of paired sample t-tests for these analyses.

The influence of different factors on PA effectiveness (research question 3) was investigated with a combination of different statistical tests. When considering the individual impact of different factors, X variables characterised by continuous, ratio scale data (Size; Age; Accessibility – Elevation; Accessibility – Slope; Accessibility – Proximity to Major Roads) were subjected to linear regression analyses (Wheeler *et al*., 2004; McCarroll, 2017) to determine their relationship with AGB change (Y) within the PAs. For example, whether there is a positive relationship between PA size and AGB change, and whether this is statistically significant. On the other hand, when X variables were discrete, ordinal scale data, tests for significant difference were employed (Wheeler *et al*., 2004; McCarroll, 2017), either the independent sample t-test (Level of Protection – a) or one-way ANOVA (Level of Protection – b; Accessibility – Proximity to Major Settlements). To determine which factor(s) best explains variability in AGB change within PAs, all X variables were combined in a multiple regression model, before Akaike's Information Criterium (AIC) was used to select the best predictor(s).

2.10 <u>Case Study: Habitat disturbance in Taraba State, Nigeria</u>

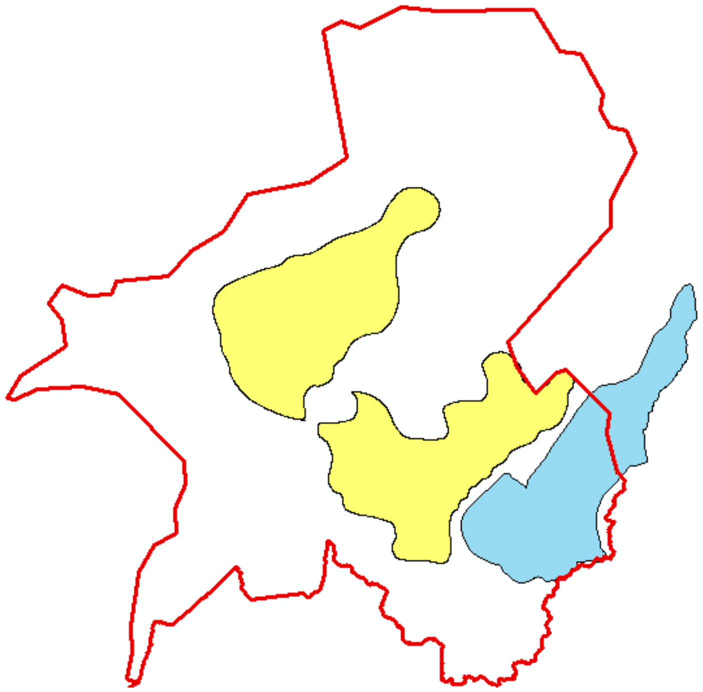


Fig. 2.6: PAs and CAs in Taraba State. The approximate border of Taraba State delineated by the red line. Although both CAs (shaded in yellow) fall within Taraba State, the northern sector of Gashaka-Gumti (shaded in blue) is located in Adamawa State.

Research question 4 entailed a focused investigation of Taraba State, a region of eastern Nigeria which borders Cameroon. Encompassing an area of approximately 60,292km^2, and with a population of over 2,300,700 (Taraba State Government, 2018), it has been devastated by illegal logging in recent years (Ahmed *et al*., 2016; Aiyetan, 2016; Chapman, 2016; Ahmed and Oruonye, 2017). Three areas formed the basis of this part of the study: Gashaka-Gumti National Park, a CA of similar size, mean elevation and mean slope to Gashaka-Gumti, and a CA of similar size but at much lower elevation and with gentler slopes to Gashaka-Gumti. Both CAs are situated within the confines of Taraba State, while the northern reaches of Gashaka-Gumti fall outside (*Fig. 2.6*). Biomass Matching was be employed to give detected and estimated AGB change for each area between 2007 and 2017, which would be essential for validating the reported woodland clearance, and assessing the potential for PAs to offer a solution to this issue. Any analyses would be purely descriptive in nature, as the sample size was far too small to warrant statistical testing.

Results

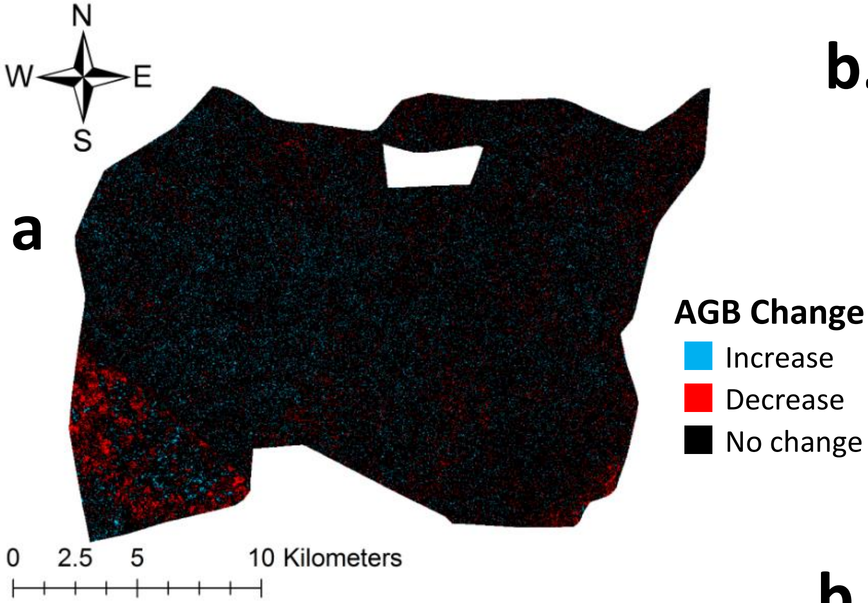
3.1 Biomass Matching – AGB Change Detection and Estimation

To test the utility of Biomass Matching for this investigation, its ability to firstly detect, and then estimate, AGB change within PAs had to be assessed. Change detection could be validated by either visual or synthetic means; the former entailed visually comparing L-band RCS data to optical remote sensing data, while the latter was performed by manipulating data in Matlab R2017a to simulate AGB loss or gain. Following these tests, the AGB changes estimated in PAs using the universal RCS-AGB relationship of this study, and then the RCS-AGB relationship of Ryan *et al*. (2012), were compared to determine how effectively Biomass Matching could estimate AGB change 2007-2017 in Nigerian PAs.

3.1.1 Detection – visual validation

The AGB Change Maps produced by Biomass Matching displayed whether pixels inside PAs between 2007 and 2017 had experienced an increase, decrease or no change in their AGB levels (*Fig. 3.1a; 3.2a*). These maps could therefore be compared to other data sources to attempt to verify whether such changes had occurred. Google Earth 7 was a particularly viable option; this version of the software comprises imagery from NASA's Landsat 7 satellite, which has been modified to minimise the presence of striped artefacts, and eliminate clouds and other atmospheric effects which might obscure the Earth's surface (Google, 2013). Additionally, the software's extensive data archive enables both past and present images of an area to be viewed with ease, so images of PAs for both 2007 and 2016/2017 could be obtained (*Fig. 3.1b; 3.2b*), visually assessed for land-cover changes over the time period, and compared to the AGB Change Maps produced by Biomass Matching.

For certain PAs, this method was a moderately robust means of validating AGB changes detected by Biomass Matching. For example, from optical remote sensing images of Kamuku National Park, changes in land-cover are clearly visible in its southwestern corner between 2007 and 2016, an occurrence reflected by its associated AGB Change Map as losses in AGB (*Fig. 3.1*).



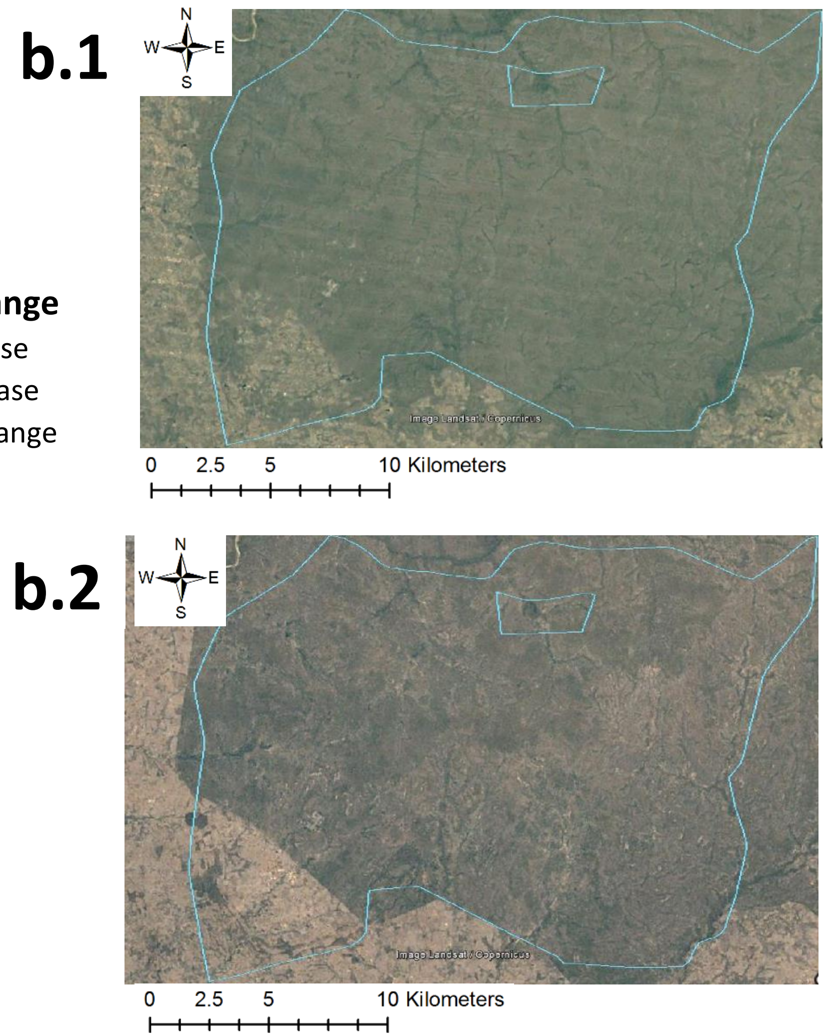
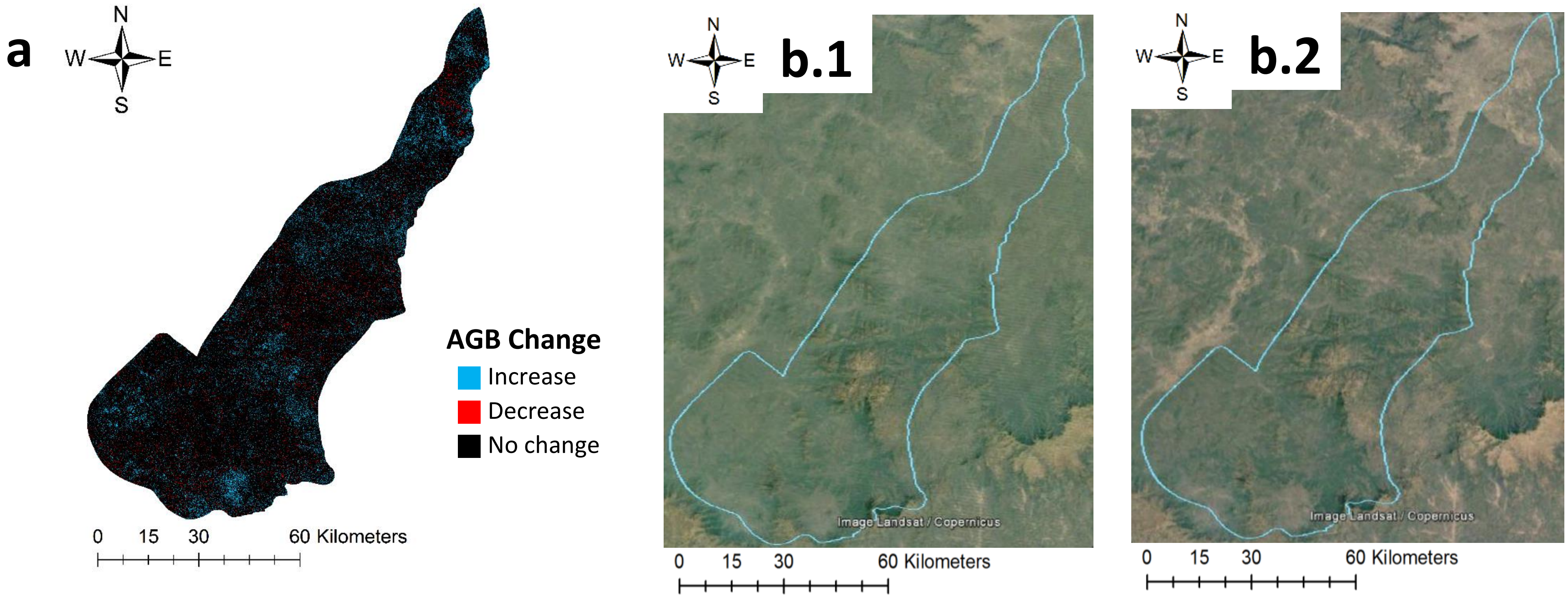


Fig 3.1: Visual Validation of Detected AGB Change for Kamuku National Park, 2007-2017. a) The AGB Change Map: blue pixels show areas of AGB gain, red pixels are areas of AGB loss, and black pixels indicate no change. b) Landsat images of Kamuku (delineated by the blue line) for 2007 (b.1) and 2016 (b.2); the detected AGB loss in the southwest corner is clearly visible (Source: Google Earth 7).


a
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Increase
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No change
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0 15 30 60 Kilometers
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Image Landsat / Copernicus
0 15 30 60 Kilometers

However, in other instances, detected AGB changes were seemingly not reflected in the Landsat images, thus rendering them wholly ineffective for validation purposes (*Fig. 3.2*). It must also be noted that such optical remote sensing data provides information on land-cover change rather than the AGB change detected by Biomass Matching (*Fig. 3.1*; *3.2*). The overall utility of this method was therefore somewhat limited.

3.1.2 Detection – synthetic validation

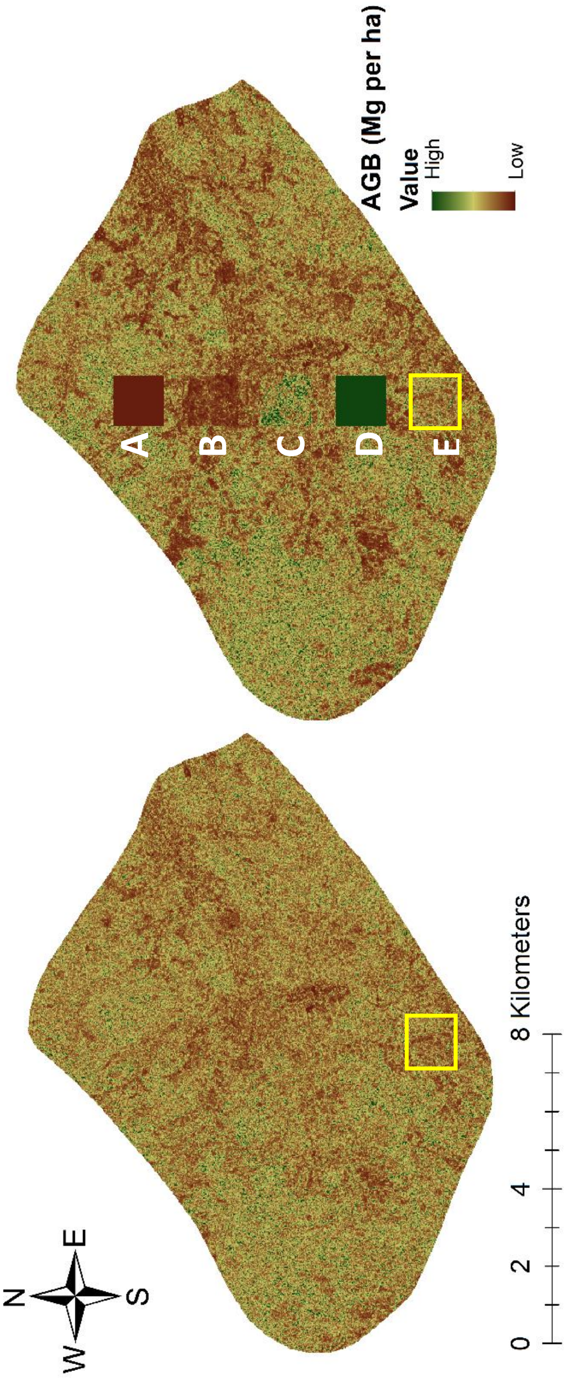


Fig. 3.3: Synthetic Validation. The yellow square indicates the control area, where 'no change' was simulated to have occurred between 2016 (left) and 2017 (right). The letters (A-E) correspond to areas in which different levels of AGB change have been simulated – 100% AGB loss (A); 50% AGB loss (B); 50% AGB gain (C); 100% AGB gain (D); no change (E).

Simulating AGB change within a PA by manipulating the processed L-band SAR data used for Biomass Matching potentially presented a far more robust means of validation. Using Opandha, a PA with high mean AGB levels per hectare, different levels of AGB change were simulated in designated areas between 2016 and 2017 (*Fig. 3.3*). The results of these tests are included in *Table 3.1*. It is quite clear from the above figures that the Biomass Matching approach is able to detect the synthetic AGB changes, and the 'Results – Mean AGB' column in *Table 3.1* quantifies the effect of the changes on mean AGB (Mg ha^{-1}) values in each treatment area. This supports the argument that the approach is an effective means of detecting AGB change within an area over time.

Table 3.1: Synthetic Validation Results. Each scenario was applied to an area of 50x50 pixels for the 2017 RCS data for Opandha before subjecting the full suite of data (2007-2017) to Biomass Matching. A brief visual interpretation is given for each scenario, as well estimated AGB levels of each treatment.

Site	**Scenario**	**Synthetic Test (applied to pixels)**	**Results (visual interpretation)**	**Results – Mean AGB (Mg ha^{-1})**
A	100% AGB loss	Pixel values = 0.005	AGB values the lowest possible	0.48
B	50% AGB loss	Pixel values = ÷2	AGB values noticeably lower than surroundings	1.12
C	50% AGB gain	Pixel values = ×2	AGB values noticeably higher than surroundings	4.13
D	100% AGB gain	Pixel values = 1	AGB values the highest possible	42.16
E	No change	Pixel values = 2016 values	Identical to corresponding area on 2016 change map	2.63

3.1.3 Estimation

Following confirmation of Biomass Matching's ability to effectively detect AGB change, the extent to which it could effectively estimate AGB change over time was assessed. To test this, the AGB change values between 2007 and 2017 –

Table 3.2: AGB Change between 2007 and 2017 for the two RCS-AGB Relationships, as well as the difference in overall (Mg), Mg ha^{-1} and % AGB change predicted for all PAs by the two equations.

	Universal RCS-AGB relationship		**Ryan et al (2012)'s RCS-AGB relationship**		**Difference between Universal and Ryan *et al* AGB Change**	
Protected Area	**AGB Change 1) Overall (Mg) 2) Mg ha^{-1}**	**% AGB Change**	**AGB Change 1) Overall (Mg) 2) Mg ha^{-1}**	**% AGB Change**	**AGB Change 1) Overall (Mg) 2) Mg ha^{-1}**	**% AGB Change**
Alawa	1) +39,389 2) +1.21	+3.86	1) +52,753 2) +1.62	+2.69	1) -13,364 2) -0.41	1.18
Dagida	1) +21,976 2) +0.58	+10.23	1) +26,928 2) +0.71	+2.88	1) -4952 2) -0.13	7.35
Ebbe/Kam-pe	1) -31,254 2) -0.32	-1.03	1) -40,870 2) -0.42	-0.70	1) -9616 2) -0.10	0.33
Falgore (Kogin Kano)	1) +107,343 2) +1.85	+12.54	1) +152,920 2) +2.64	+7.08	1) -45,577 2) -0.79	5.46
Gashaka-Gumti	1) +2,094,774 2) +3.44	+9.45	1) +3,296,872 2) +5.42	+8.04	1) -1,202,098 2) -1.98	1.41
Ifon	1) +72,055 2) +1.40	+5.27	1) +106,812 2) +2.08	+3.87	1) -34,757 2) -0.68	1.40
Kainji Lake	1) +241,413 2) +0.40	+6.80	1) +403,624 2) +0.66	+2.67	1) -162,211 2) -0.26	4.13
Kamuku	1) +8840 2) +0.24	+1.94	1) +12,950 2) +0.36	+1.04	1) -4110 2) -0.12	0.90
Kashimbila	1) +401,636 2) +3.64	+10.64	1) +561,711 2) +5.09	+7.92	1) -160,075 2) -1.45	2.72
Kogo	1) -380 2) -0.006	-0.11	1) -12,200 2) -0.18	-0.77	1) -11,820 2) -0.174	0.66
Kuyamban-a	1) +198,858 2) +1.11	+5.48	1) +299,905 2) +1.68	+3.73	1) -101,047 2) -0.57	1.75
Lame-Burra	1) -77,211 2) -0.32	-1.43	1) -75,459 2) -0.31	-0.65	1) 1752 2) 0.01	-0.78
Meko	1) +172,642 2) +0.23	+8.0	1) +298,360 2) +3.85	+6.94	1) -125,718 2) -3.62	1.06
Ohosu	1) +123,763 2) +2.42	+7.47	1) +181,190 2) +3.54	+5.74	1) -57,427 2) -1.12	1.73
Opandha	1) +28,252 2) +2.41	+5.85	1) +39,537 2) +3.37	+4.56	1) -11,285 2) -0.96	1.29
Opara	1) +129,896 2) +0.58	+2.42	1) +246,551 2) +1.10	+2.20	1) 116,655 2) -0.52	0.22
Orle River	1) +56,204 2) +1.20	+5.53	1) +67,428 2) +1.44	+3.07	1) -11,224 2) -0.24	2.46
Pandam and Wase Lakes	1) -27,582 2) -1.34	-6.69	1) -38,889 2) -1.89	-4.24	1) 11,307 2) 0.55	-2.45

Udi/Nsukk-a	1) +24,487 2) +1.39	+5.07	1) +35,534 2) +2.02	+3.68	1) -11,047 2) -0.63	1.39
Upper Ogun/ Old Oyo	1) +281,137 2) +1.14	+4.06	1) +414,005 2) +1.68	+3.01	1) -132,868 2) -0.54	1.05
Yankari	1) +524,000 2) +2.35	+29.31	1) +1,109,400 2) +17.40	+28.00	1) -585,400 2) -15.05	1.31

in Mg, Mg ha^{-1} and percent – produced for each PA when using two different RCS-AGB relationships were compared: firstly, the coefficients used in this study (see section 2.5), and secondly, those used in Ryan *et al*. (2012)'s study of AGB change in Mozambican miombo woodland (*Table 3.2*). Furthermore, the mean AGB change 2007-2017 estimated for all PAs using each of the RCS-AGB relationships were plotted on a single figure (*Fig. 3.4*a), along with that for a single PA – Kamuku (*Fig. 3.4*b). This allowed a comparison of the trends in AGB change estimated by the two sets of coefficients.

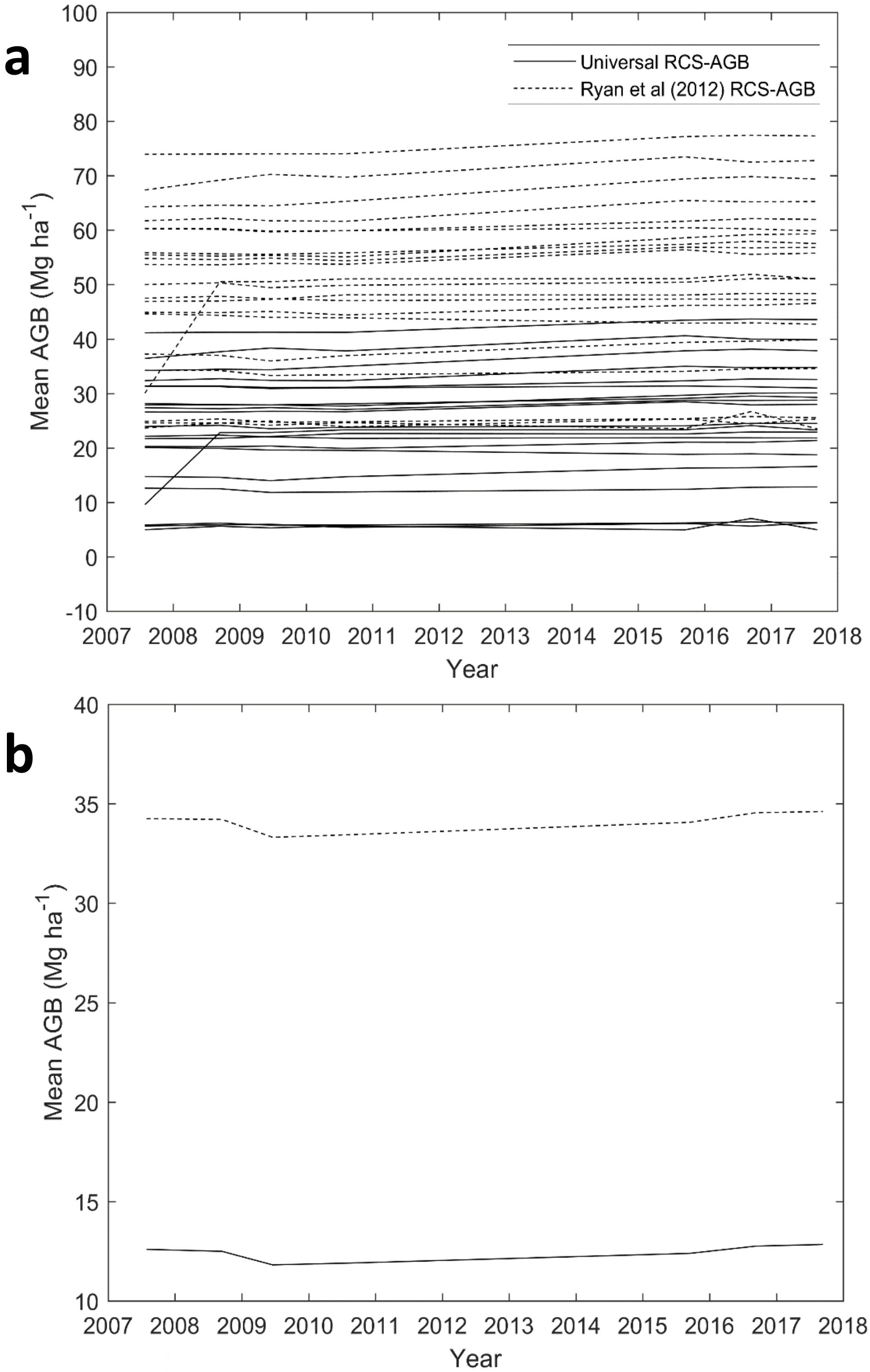


Fig. 3.4: These plots show the disparities in mean AGB levels estimated for each PA using the different RCS-AGB relationships. a) AGB Change Estimation – including all 21 PAs in the study; (b) AGB Change Estimation – focusing on Kamuku; this shows how, despite the higher mean AGB estimated by the Ryan *et al*. (2012) coefficients, the trend in AGB change over time is almost identical.

Discrepancies in the AGB change values estimated by the two RCS-AGB relationships are immediately apparent. The Ryan *et al*. (2012) coefficients (with the exception of Lame-Burra) consistently estimate greater AGB change (both positive and negative) to have occurred between 2007 and 2017 (*Table 3.2*), though an independent samples t-test – $t(38) = -1.110$, $p = 0.274$ – does not find a statistically significant difference between mean Mg ha^{-1} change values for the two datasets at the 0.05 significance level. However, *Fig. 3.4*a emphasises these differences by displaying the disparities between mean AGB changes for all PAs when using the different RCS-AGB relationships for Biomass Matching, with *Fig. 3.4*b showing how for each PA, the nature of these changes over time are visually identical.

3.2 Effectiveness of Protected Areas vs. Control Areas

Table 3.3: AGB Levels and Changes Estimated by Biomass Matching. For the size class of each PA: S = small; M = medium; L = Large; VL = very large.

Protected Area (size class)	**Area (ha)**	**2007 AGB 1) Mg 2) Mg ha^{-1}**	**2017 AGB 1) Mg 2) Mg ha^{-1}**	**AGB Change 1) Mg 2) Mg ha^{-1}**	**% AGB Change (2007 – 2017)**
Alawa (S)	32,530	1) 1,020,500 2) 31.37	1) 1,059,900 2) 32.58	1) +39,389 2) +1.21	+3.86
Dagida (S)	38,022	1) 214,791 2) 5.65	1) 236,770 2) 6.23	1) +21,976 2) +0.58	+10.23
Ebbe/Kampe (M)	97,276	1) 3,047,368 2) 31.33	1) 3,016,114 2) 31.01	1) -31,254 2) -0.32	-1.03
Falgore (M)	58,034	1) 855,950 2) 14.75	1) 963,290 2) 16.60	1) +107,343 2) +1.85	+12.54
Gashaka-Gumti (VL)	608,410	1) 22,165,936 2) 36.44	1) 24,260,710 2) 39.88	1) +2,094,774 2) +3.44	+9.45
Ifon (M)	51,410	1) 1,367,000 2) 26.59	1) 1,439,100 2) 27.99	1) +72,055 2) +1.40	+5.27
Kainji Lake (VL)	607,870	1) 3,552,600 2) 5.84	1) 3,794,000 2) 6.24	1) +241,413 2) +0.40	+6.80
Kamuku (S)	36,220	1) 456,210 2) 12.60	1) 465,050 2) 12.84	1) +8840 2) +0.24	+1.94
Kashimbila (M)	110,310	1) 3,774,100 2) 34.21	1) 4,175,700 2) 37.86	1) +401,636 2) +3.64	+10.64
Kogo (M)	67,010	1) 333,510 2) 4.98	1) 333,130 2) 4.97	1) -380 2) -0.006	-0.11

Kuyambana (M)	178,990	1) 3,626,200 2) 20.26	1) 3,825,040 2) 21.37	1) +198,858 2) +1.11	+5.48
Lame-Burra (L)	244,460	1) 5,409,500 2) 22.13	1) 5,332,336 2) 21.81	1) -77,211 2) -0.32	-1.43
Meko (M)	77,460	1) 2,159,200 2) 27.88	1) 2,331,900 2) 30.11	1) +172,642 2) +2.23	+8.0
Ohosu (M)	51,155	1) 1,655,700 2) 32.37	1) 1,779,500 2) 34.79	1) +123,763 2) +2.42	+7.47
Opandha (S)	11,733	1) 482,910 2) 41.16	1) 511,160 2) 43.57	1) +28,252 2) +2.41	+5.85
Opara (L)	224,080	1) 5,361,900 2) 23.93	1) 5,491,800 2) 24.51	1) +129,896 2) +0.58	+2.42
Orle River (S)	46,842	1) 1,016,700 2) 21.70	1) 1,072,897 2) 22.90	1) +56,204 2) +1.20	+5.53
Pandam and Wase Lakes (S)	20,546	1) 412,250 2) 20.06	1) 384,660 2) 18.72	1) -27,582 2) -1.34	-6.69
Udi/Nsukka (S)	17,621	1) 482,610 2) 27.39	1) 507,100 2) 28.78	1) +24,487 2) +1.39	+5.07
Upper Ogun/ Old Oyo (L)	246,300	1) 6,931,101 2) 28.14	1) 7,212,238 2) 29.28	1) +281,137 2) +1.14	+4.06
Yankari (L)	222,630	1) 1,789,800 2) 8.05	1) 2,313,800 2) 10.40	1) +524,000 2) +2.35	+29.31
Control Area					
Small 1	47,733	1) 441,220 2) 9.24	1) 408,300 2) 8.55	1) -32,918 2) -0.69	-7.46
Small 2	14,536	1) 272,500 2) 18.75	1) 283,120 2) 19.48	1) +10,620 2) +0.73	+3.90
Small 3	28,327	1) 35,640 2) 1.26	1) 58,723 2) 2.07	1) +23,083 2) +0.81	+64.76
Medium 1	171,990	1) 497,080 2) 2.89	1) 354,100 2) 2.06	1) -143,190 2) -0.83	-28.81
Medium 2	85,782	1) 863,540 2) 10.07	1) 965,491 2) 11.26	1) +101,951 2) +1.19	+11.81
Medium 3	111,820	1) 760,570 2) 6.80	1) 826,720 2) 7.39	1) +66,150 2) +0.59	+8.70
Large 1	314,130	1) 1,377,800 2) 4.39	1) 730,992 2) 2.33	1) -646,808 2) -2.06	-46.95
Large 2	224,710	1) 3,010,752 2) 13.40	1) 3,095,948 2) 13.78	1) +85,196 2) +0.38	+2.83

Large 3	428,950	1) 2,999,100 2) 6.99	1) 3,438,912 2) 8.02	1) +440,912 2) +1.03	+14.66
Very Large 1	618,090	1) 24,711,518 2) 39.98	1) 26,906,778 2) 43.53	1) +2,195,260 2) +3.55	+8.88
Very Large 2	640,120	1) 2,675,312 2) 4.18	1) 1,862,400 2) 2.91	1) -812,912 2) -1.27	-30.39
Very Large 3	617,300	1) 6,300,700 2) 10.21	1) 6,110,886 2) 9.90	1) -189,820 2) -0.31	-3.01

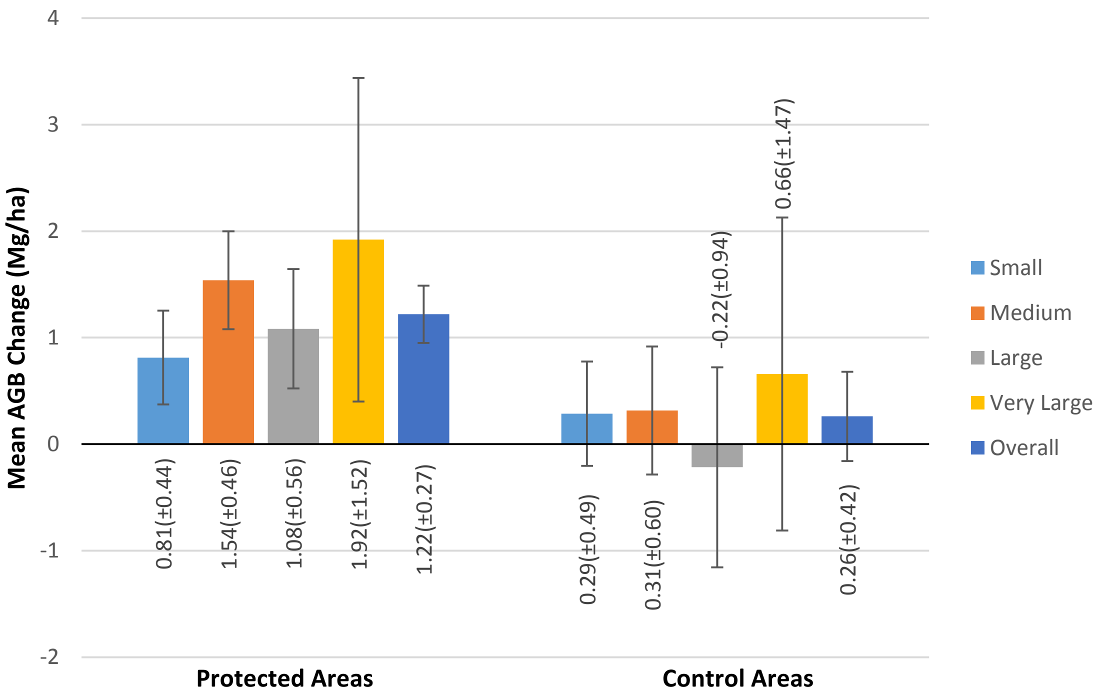


Fig. 3.5: Bar Graph of Mean AGB Change 2007-2017 in PAs and CAs. Mean AGB change and standard error (SE) are given beside the column representing each category, though independent samples t-tests did not find significant differences (p<0.05) between PA and CA means for any category; the results are reported below:

Small: t = 0.696(8), p = 0.51
Medium: t = 1.45(9), p = 0.18
Large: t = 1.13(5), p = 0.31
Very Large: t = 0.57(3), p = 0.61
Overall: t = 1.99(31), p = 0.06

To determine whether this sample of Nigerian PAs was effective in conserving (and enhancing) AGB levels over time, the mean per hectare AGB change was compared with that estimated for a set of twelve unprotected CAs. Furthermore, both the PAs and CAs could be subjectively subdivided into groups according to their size in hectares: ‘Small’ (0 – 50,000), ‘Medium’ (50,001 – 200,000), ‘Large’ (200,001 – 500,000) and ‘Very Large’ (>500,000). The mean AGB change values for these equivalent PA and CA groups could then also be compared through statistical testing. Estimated AGB levels and AGB changes for each PA and CA are recorded in *Table 3.3*, while the mean AGB change values and outcomes of subsequent statistical tests are reported in *Fig. 3.5*. The differences between PAs and CAs in terms of AGB change

2007-2017 are further visualised by *Fig. 3.6*.

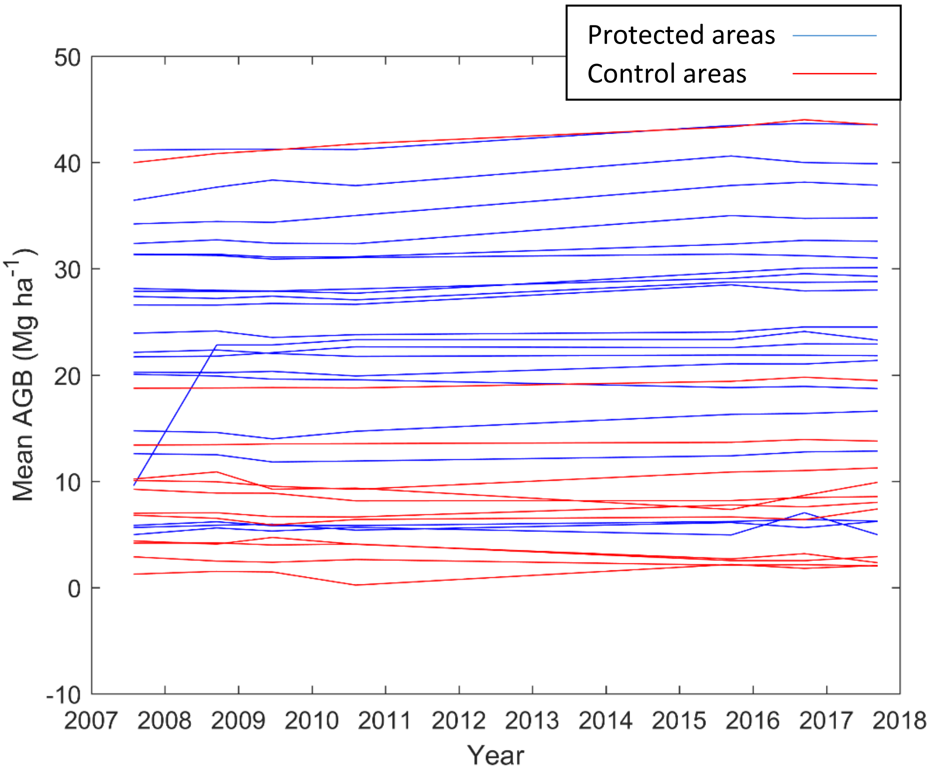


Fig 3.6: Mean AGB Change 2007-2017. This displays estimates for the 21 PAs (blue lines) and 12 CAs (red lines) included in the study.

The AGB change dataset met the requirements for parametric statistical testing: it is measured on a continuous scale, normally distributed according to the Shapiro-Wilk test (F = 0.978(33), p = 0.735), and Levene’s test found there to be homogeneity of variances: F = 0.134(1,31), p = 0.717. Consequently, independent samples t-tests were undertaken to assess for statistically significant difference between the mean AGB change values overall, and for each size category (Wheeler *et al*., 2004).

Clear disparities are visible between the mean AGB change values for PAs and CAs across all groups, with change in PAs consistently more positive than in unprotected CAs; indeed this is most starkly visible for the ‘Large’ category, where mean AGB levels in PAs increased from 2007 to 2017, whilst the CAs experienced AGB loss (*Fig. 3.5*). Although these visual comparisons suggest PAs of all size groups – and therefore, overall – to be more effective than similar unprotected areas for conserving and enhancing AGB, the independent samples t-tests found no significant difference in AGB Change between PAs and CAs on any occasion (*Fig. 3.5*). Consequently, the null hypothesis of no statistically significant difference in per hectare AGB change between PAs and CAs must be accepted for each size category, and overall.

3.3 <u>Factors Influencing Protected Area Effectiveness</u>

Statistical analyses were undertaken in order to determine a) the strength and direction of relationships between individual factors and AGB change, and b) which of the following factors might exert the greatest influence on AGB change within the sample of Nigerian PAs (*Table 3.5*). The type of analysis was dictated by the properties of the data. Explanatory statistics were preferable, and therefore linear and multiple regression were employed if requirements were met: the data was on a continuous scale of measurement; it generally conformed to a normal distribution; the relationship between variables was linear; the sample size was sufficiently large (over 20); outliers were absent or minimal; there was independence of residuals (only applicable for multiple regressions); data were generally homoscedastic (McCarroll, 2017). If data were not continuous, and therefore regression analysis was not possible, tests for statistically significant difference were undertaken instead. Parametric tests – independent samples t-test and ANOVA – were undertaken if conditions of normality and homoscedasticity were met; if not, the non-parametric equivalents of Mann-Whitney U and Kruskal-Wallis were used instead. Regression analyses tested the null hypothesis of *‘there is no statistically significant relationship between the independent variable(s) and AGB change over time’*, while tests for significant difference assessed the null hypothesis of '*there is no statistically significant difference in the AGB change values between groups*' . The final stage of the analysis was to combine all factors in a multiple regression to determine which variable(s) best explains variability in AGB change over time.

Table 3.5: Statistical Analyses for Research Question 3. Linear regression tested for the presence of a significant relationship between each factor and per hectare AGB change within PAs, while independent samples t-tests, one-way ANOVA and Kruskal-Wallis tested for significant difference between groups, from which a link to AGB change could be inferred.

	Statistical Test	**R^2 value (Adjusted R^2)**	**Significa-nce value**	**Null Hypothesis**
Size	Linear regression	0.024	0.504	Accept
Age	Linear regression	0.096	0.172	Accept
Level of Protection – a) Strict Protection/Mixed-use; b) IUCN Categories	a) Independent Samples t-test; b) One-way ANOVA	N/A	a) 0.689 b) 0.906	a) Accept b) Accept
Accessibility – Elevation	Linear regression	0.012	0.635	Accept
Accessibility – Slope	Linear regression	0.419	0.001	Reject
Accessibility – Proximity to Major Settlements	Kruskal-Wallis	N/A	0.697	Accept
Accessibility – Proximity to Major Roads	Linear regression	0.030	0.455	Accept

3.3.1 Size

Having met the assumptions for linear regression, PA size was regressed against AGB change (Mg ha-1) to determine the strength and direction of any relationship between them.

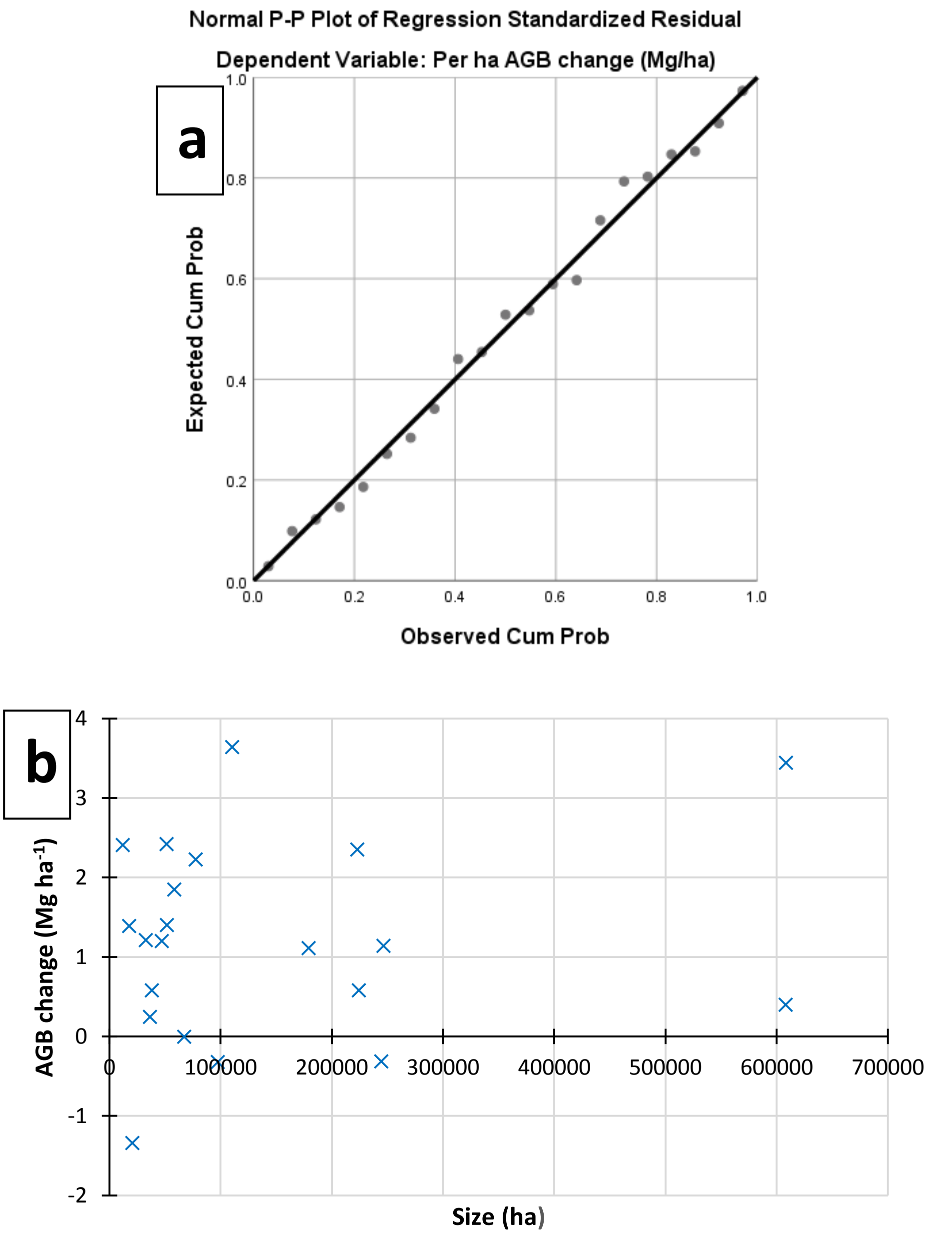


Fig 3.7: PA Size and AGB change 2007-2017. a) the P-P plot showing the data to follow a normal distribution, and b) the scatterplot of PA size vs. AGB change. The regression equation is y = 1E-06x + 1.0561.

There was no significant relationship between size (ha) and AGB change: $F(1,19) = 0.464$, $p = 0.504$, and $R^2 = 0.024$ shows size to explain only 2.4% of variance in AGB change. It cannot therefore be confidently stated whether small or large PAs were more effective at protecting and enhancing AGB within this set of PAs.

3.3.2 Age

Having met the assumptions for linear regression, PA age was regressed against AGB change.

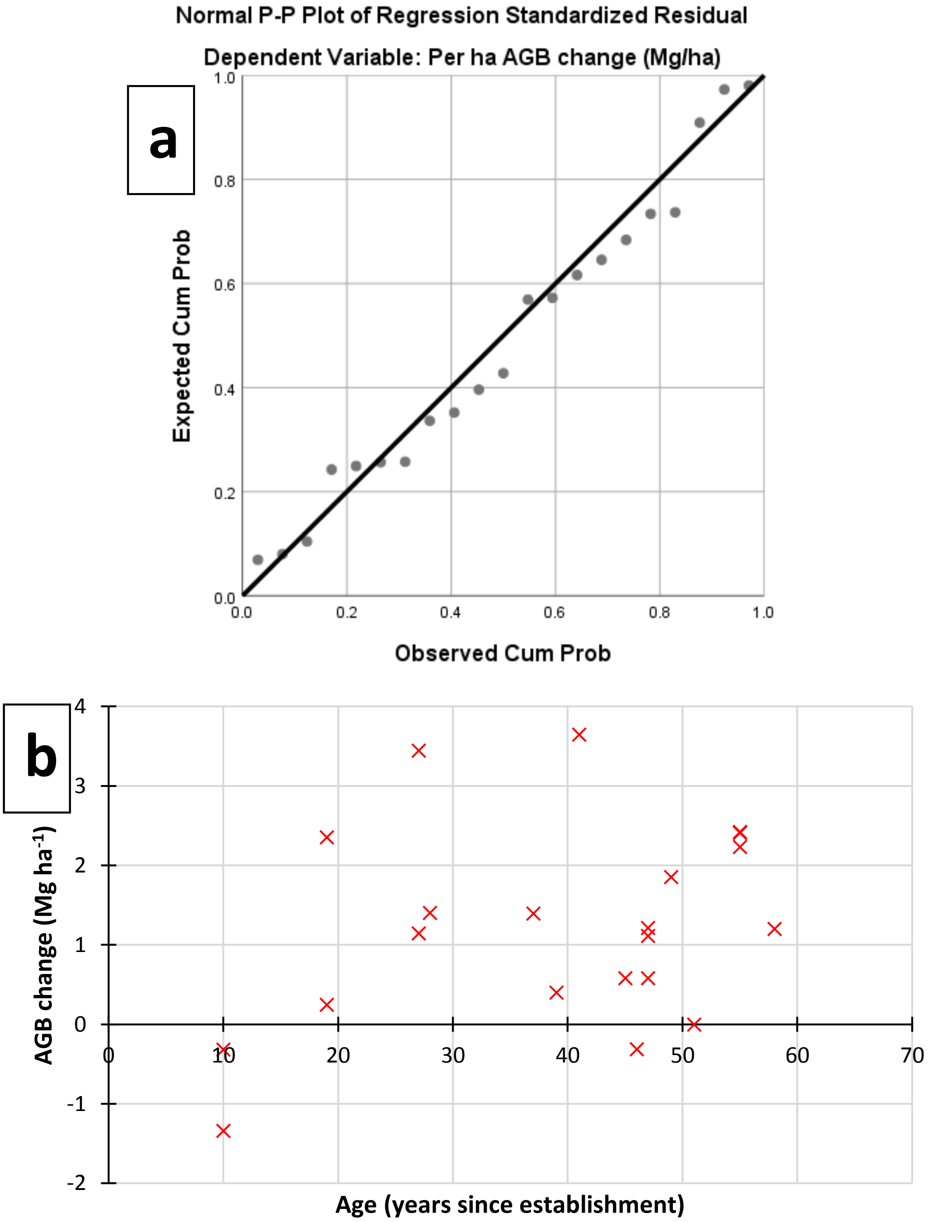


Fig 3.8: PA Age and AGB change 2007-2017. a) the P-P plot showing the data to follow a normal distribution, and b) the scatterplot of PA age vs. AGB change. The regression equation is y = 0.0259x + 0.2196.

There was no significant relationship between the two variables: $F(1,19)$ = 2.017, p = 0.172, and R^2 = 0.096 shows age to explain only 9.6% of the variance in AGB change. However, age was found to positively influence AGB change within PAs, with AGB increasing by 0.026 Mg ha^{-1} for each year since establishment.

3.3.3 Level of Protection

As this dataset was discrete in nature, tests for significant difference were undertaken for the two categorisation approaches which were adopted. The Strict Protection/Mixed-Use grouping was informed by the likes of Nelson and Chomitz (2011) and Blackman *et al*. (2015): PAs designated as National Parks and Ramsar Sites (wetlands of international importance) were placed in the 'Strict Protection' category, while all others were deemed 'Mixed-Use'. Alternatively, the IUCN Categories approach grouped PAs according to whether they were listed as IUCN II and Ramsar Site, IUCN IV, or Forest/Game Reserves.

Assumptions of normality and homogeneity were met for both subsets of data. The Strict Protection/Mixed-Use approach returned Shapiro-Wilk results of $F(6) = 0.980$, $p = 0.952$, for the 'Strict Protection' group, and $F(15) = 0.961$, $p = 0.703$ for the 'Mixed-Use' group, along with a Levene's result of $F(19) = 1.374$, $p = 0.256$ for the data as a whole. The IUCN Categories approach returned Shapiro-Wilk results of $F(6) = 0.980$, $p = 0.952$; $F(5) = 0.971$, $p = 0.881$; $F(10) = 0.928$, $p = 0.429$ for the 'IUCN II and Ramsar Site', 'IUCN IV' and 'Forest/Game Reserves' groups respectively, with a Levene's result of $F(2,18) = 1.036$, $p = 0.375$. Consequently, the parametric independent samples t-test and one-way ANOVA were applied to the respective subsets of data.

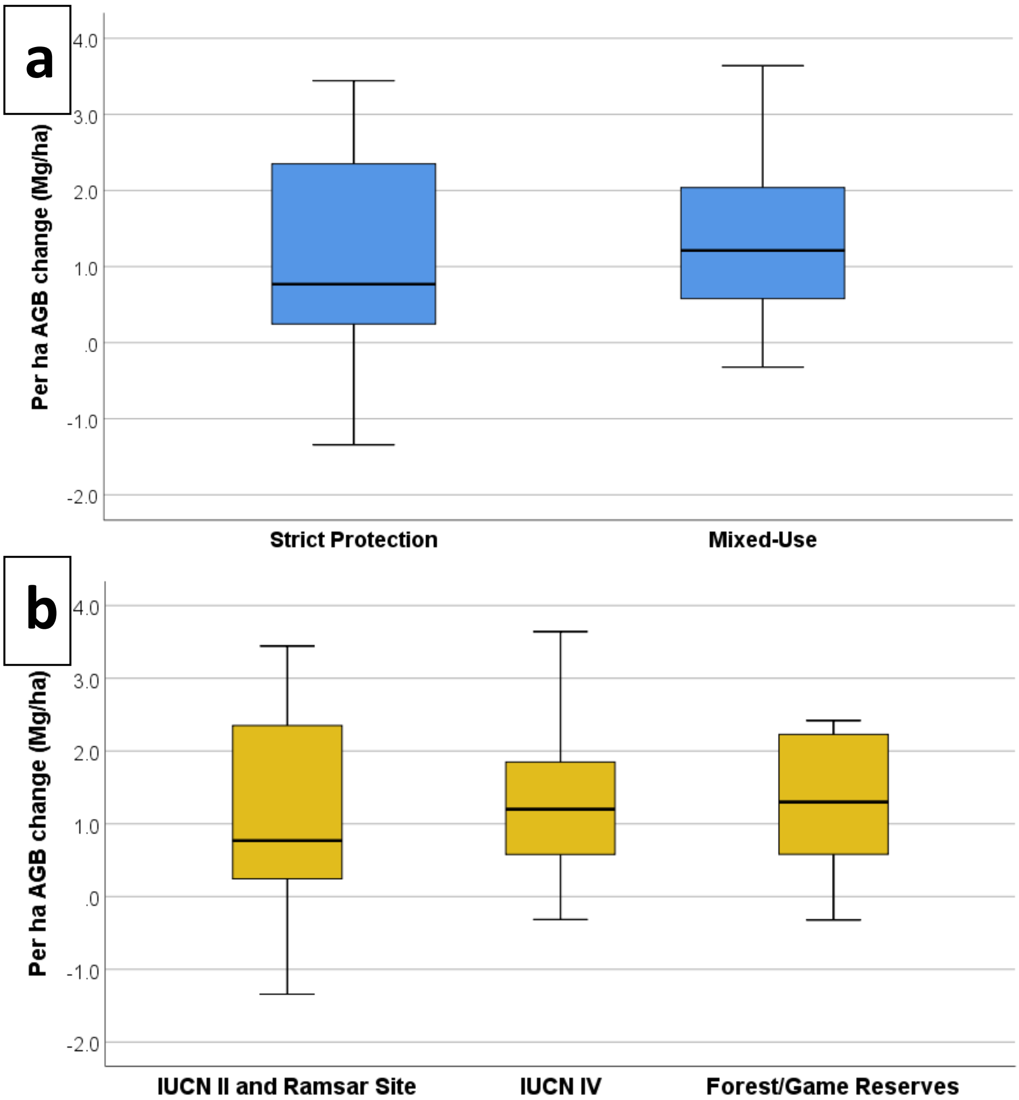


Fig 3.9: Level of Protection and AGB Change 2007-2017. a) The Strict Protection/Mixed-Use grouping, where mean AGB change was 1.04(±0.69) and 1.29(±0.29) for 'Strict Protection' and 'Mixed-Use' categories respectively. b) The IUCN Categories grouping, where mean AGB change was 1.04(±0.69) for 'IUCN II and Ramsar sites', 1.39(±0.67) for 'IUCN IV', and 1.24(±0.30) for 'Forest/Game Reserves'.

The statistical tests reported no significant difference between groups for either categorisation approach: the independent samples t-test returned $t(19) = -0.407$, $p = 0.689$, and one-way ANOVA $F(2,18) = 0.100$, $p = 0.906$. However, the outputs suggest that less restrictive PAs are more effective at conserving and enhancing AGB in both instances; this is particularly as 'Mixed-Use' PAs recorded higher mean AGB change (0.25 Mg ha^{-1} higher) for the Strict Protection/Mixed-Use approach, while 'IUCN IV' PAs had the highest mean AGB change for the IUCN categorisation (*Fig 3.9*).

3.3.4 Accessibility

The environmental variables of Elevation, Slope, Proximity to Major Settlements, and Proximity to Major Roads, were each analysed in turn to ascertain how they might influence AGB change within PAs. Regression analyses were undertaken for Elevation, Slope and Proximity to Major Roads, while a test for significant difference was required for Proximity to Major Settlements.

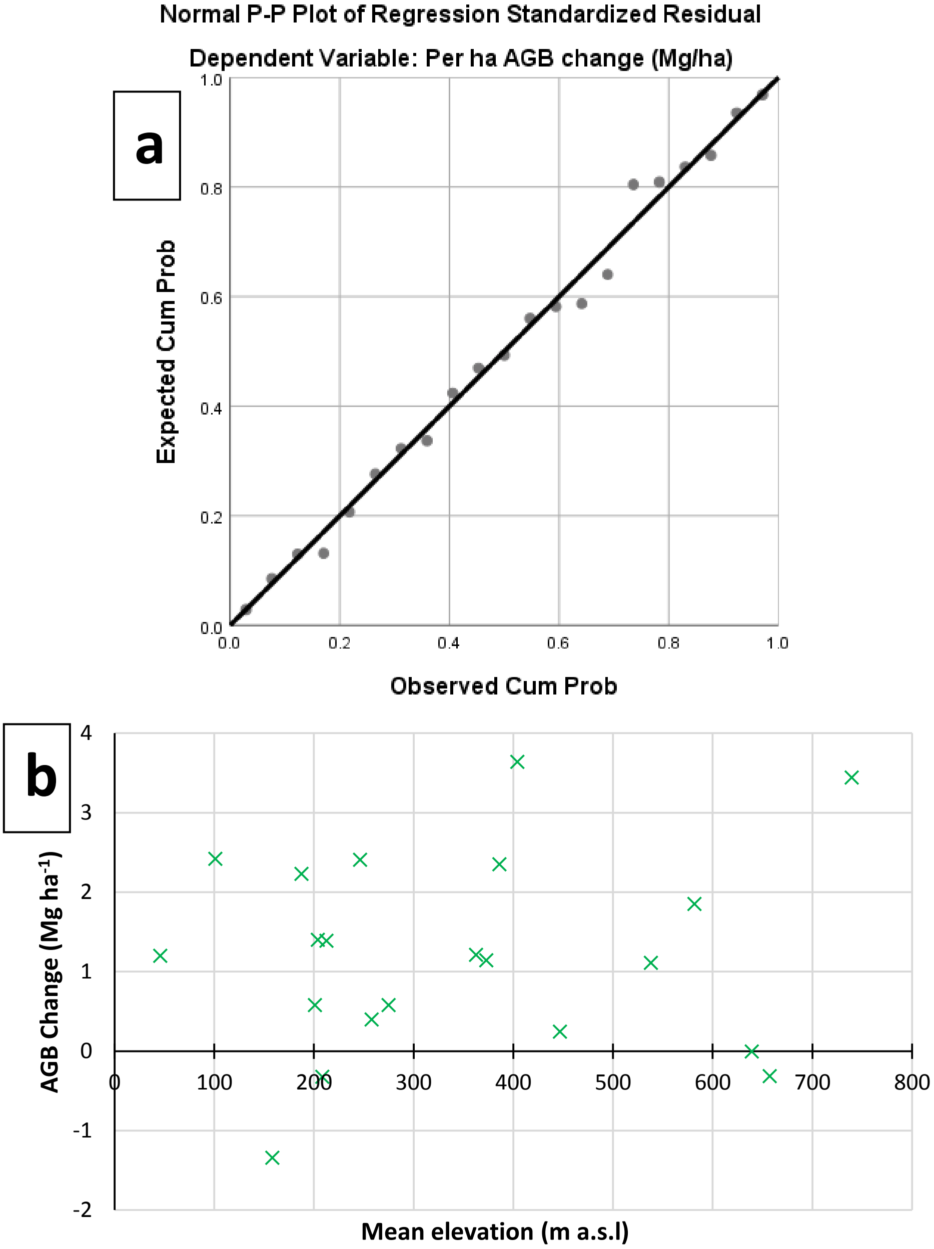


Fig. 3.10: Mean PA Elevation and AGB Change 2007-2017. a) The P-P plot showing the data to follow a normal distribution, and b) mean PA elevation vs. AGB Change (Mg ha^{-1}), where elevation is given in metres above sea-level (m a.s.l). The regression equation is y = 0.0007x + 0.9744.

Having passed the requirements for normality and homogeneity, mean PA Elevation was regressed against AGB change. There was however, no significant relationship between the two variables: $F(1,19) = 0.233$, $p = 0.635$, and $R^2 = 0.012$ showed there to be little discernible impact of elevation on AGB change within a PA (*Fig. 3.10*).

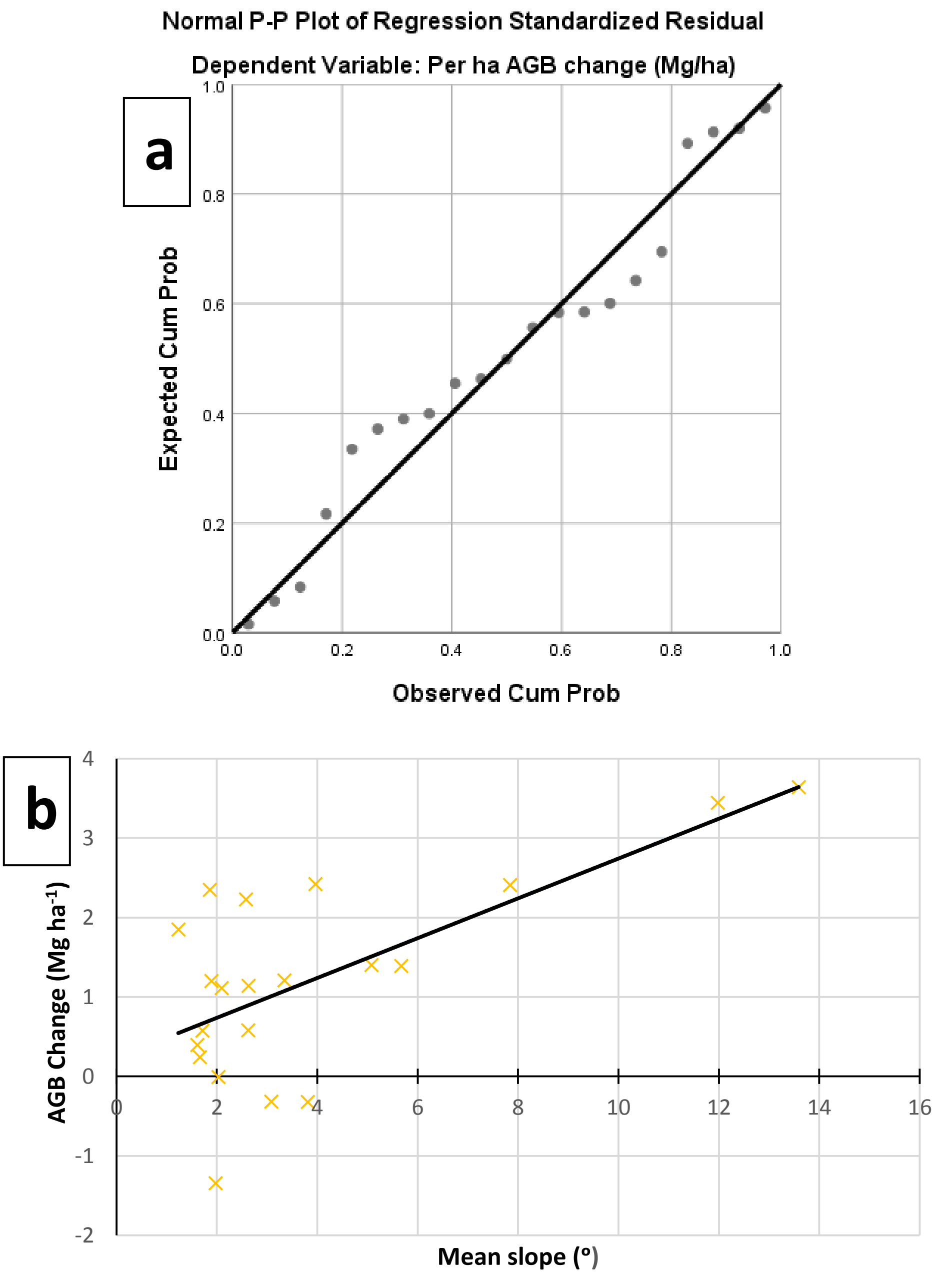


Fig. 3.11: Mean PA Slope and AGB Change 2007-2017. a) The P-P plot showing the data to follow a normal distribution, and b) mean PA slope vs. AGB Change (Mg ha^{-1}), where slope is given in degrees (º). The regression equation is y = 0.2505x + 0.2384.

The data for mean PA slope and AGB change met the requirements for normality and homogeneity, so a linear regression was undertaken. A significant relationship was present between the two variables at the 99.9% confidence interval $F(1,19) = 15.419$, $p = 0.001$, and $R^2 = 0.419$ showed slope to predict 41.9% of the variance of PA AGB. The results strongly suggest that PAs with steeper slopes are more effective at conserving and enhancing AGB within PAs, with AGB increasing by 0.25 Mg ha^{-1} for every additional degree in mean PA slope (*Fig. 3.11*).

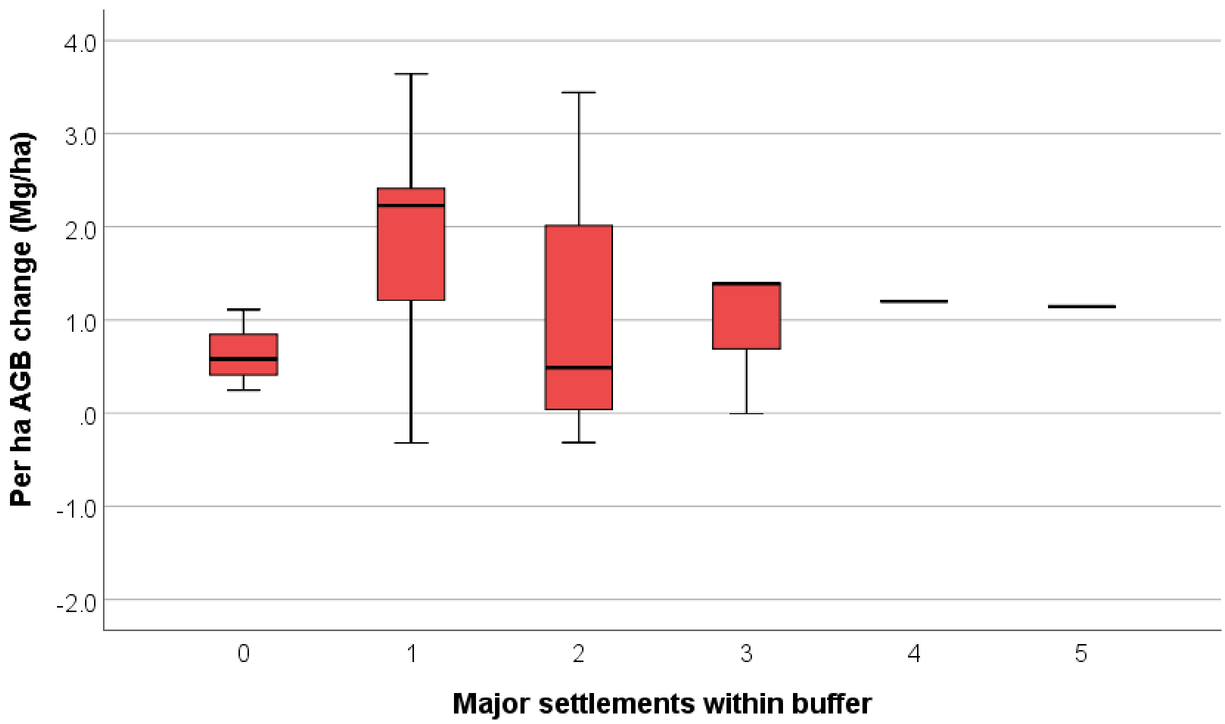


Fig. 3.12: Proximity to major settlements and AGB Change 2007-2017. This was determined by the number of settlements within a PA and its associated buffer zone. Mean AGB change (Mg ha^{-1}) was as follows for each category: 0 = 0.65; 1 = 1.60; 2 = 1.03; 3 = 0.93. 4 and 5 contained only one PA; their AGB changes were 1.20 and 1.14 respectively.

The dataset for Proximity to Major settlements and PA AGB change did not meet all requirements normality, with the category for 3 settlements within a buffer deviating significantly from a normal distribution at the 99% confidence interval: Shapiro-Wilk $F(3) = 0.756$, $p = 0.014$. The non-parametric Kruskal-Wallis test was therefore undertaken, but no significant difference was found to exist between the means of the different categories, with a significance value of 0.697. The presence of settlements within PAs (and their associated buffer zones) appeared to have little impact on the AGB change experienced over time (*Fig. 3.12*).

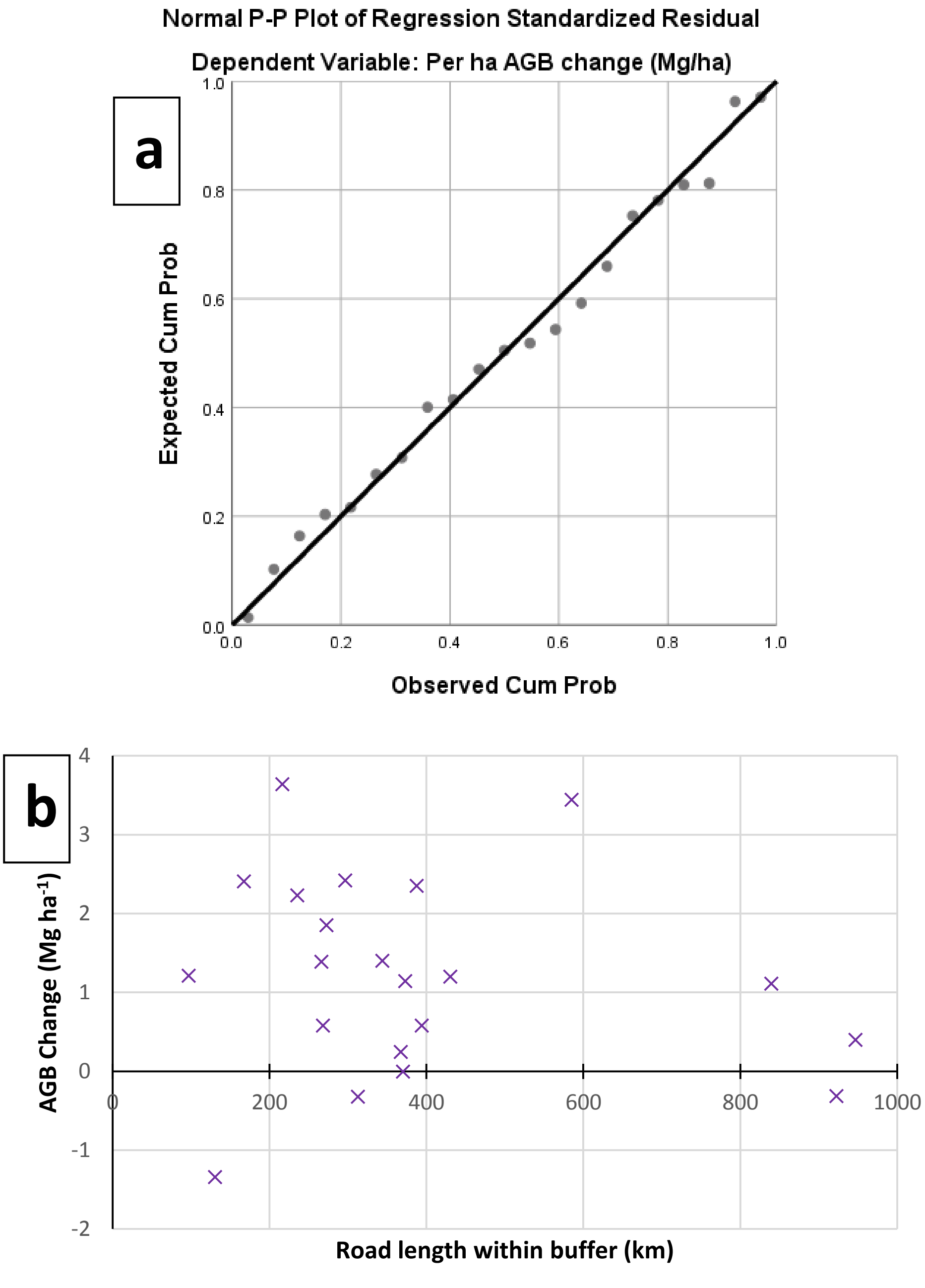


Fig. 3.13: Proximity to Major Roads and AGB Change 2007-2017. a) The P-P plot showing the data to follow a normal distribution, and b) road length within each PA (and its associated buffer zone) vs. AGB Change (Mg ha^{-1}), where length is given in kilometres (km). The regression equation is y = -0.0009x + 1.5729.

Linear regression analysis was undertaken for the Proximity to Major Roads and AGB Change dataset, as it conformed to a normal distribution and was homogeneous in nature. However, there was no significant relationship between the two variables – F(1,19) = 0.582, p = 0.455 – and R^2 = 0.030

showed this factor to account for little of the variance in AGB Change within PAs. There appears to be little discernible impact of road length within PAs on how their AGB levels changed 2007-2017.

3.3.6 Most Influential Factor

Stepwise multiple regression analysis was undertaken to determine which PA characteristic exhibited the strongest effect on AGB change; 'Level of Protection' was however excluded, as neither the 'Strict Protection/Mixed-Use' or 'IUCN Categories' approaches contained interval or ratio scale data. Slope was found to exert the greatest influence on AGB change within PAs; indeed, this was the only predictor included in the model ($F(1,19) = 15.419$, $p = 0.001$), as the adjusted $R^2 = 0.419$ shows this variable alone to explain 41.9% of the variance in AGB change seen within the PAs. The model's explanatory power was not improved by including additional factors, though the $t = 2.095$ for Age ($t = 3.927$ for Slope) demonstrated how this variable was also an important predictor of PA effectiveness. The multiple regression equation can be written as $Y(AGB\ change) = 0.238 + 0.251(Mean\ Slope)$; full outputs of the stepwise regression are included in Appendix C.

Discussion

4.1 Biomass Matching – detecting and estimating AGB change

4.1.1 Detection

When assessing whether Biomass Matching is an effective approach for predicting AGB change from L-band SAR data, it must first be ascertained if it can effectively detect whether individual pixels have experienced either increases or decreases in AGB between two time points. Visually comparing the AGB change maps produced by the process to alternative data sources (*Fig. 3.1; 3.2;* Appendix B) was one of the options available to do this.

Optical remote sensing data – such as that freely available through Google Earth – offers one potential means of validating such AGB changes, and is perfectly viable should circumstances allow. For some PAs, including Kamuku (*Fig. 3.1*), Kainji Lake and Upper Ogun (Appendix B), it is relatively easy to discern any areas of notable habitat change within their borders from Google Earth's Landsat data; this renders comparisons with their respective AGB Change Maps possible. Conversely, AGB changes within other PAs, such as Gashaka-Gumti (*Fig. 3.2*), are almost impossible to determine from this optical data, so here the utility of Biomass Matching for AGB change detection is limited. However, these incidences may instead be a function of the inherent differences between optical and SAR remote sensing data, rather than resulting from shortcomings with Biomass Matching. While optical remote sensing data (and Landsat in particular) can provide excellent long-term records of tropical forest-cover change (Hansen *et al*., 2013; Roy *et al*., 2014; Reiche *et al*., 2015), this is not a measure of AGB change (Thenkabail *et al*., 2004), and fusion with additional data sources is required before it is capable of detecting this (Reiche *et al*., 2015). SAR data is one such source; indeed, a strong relationship between L-band RCS and AGB has been found to exist in tropical dryland ecosystems (Mitchard *et al*., 2009; Mitchard *et al*., 2011; Ryan *et al*., 2012), so even subtle changes in the RCS from a particular area over time may be inferred as a change in AGB. This relationship between the RCS signal and AGB renders L-band SAR far more sophisticated than its optical counterparts, and explains why data obtained by the latter was unable to validate the small-scale AGB changes in PAs detected by Biomass Matching in this investigation.

On the other hand, synthetic validation procedures encounter no such issues and consistently demonstrate the robustness of the Biomass Matching approach for detecting AGB change. Rather than comparing two different data sources, the SAR data collected for a particular PA (Opandha) was manipulated to simulate varying levels of AGB loss and gain in different areas of pixels between two time points (*Fig 3.3*; *Table 3.1*). These synthetic AGB changes were successfully identified by the Biomass Matching process and visible on corresponding AGB change maps (*Fig. 3.3*), suggesting that the approach may be an effective method for detecting real-world AGB changes within an area of interest.

However, though methodologically sound, the overall utility of the approach is contingent on the appropriate radar data being employed to investigate a particular ecosystem or region. L-band SAR is arguably sensitive to any AGB changes in tropical dry forests and savannahs, where AGB levels rarely exceed 100 Mg ha^{-1}, though the exact threshold at which RCS signal sensitivity is reduced and eventually lost (Imhoff, 1993; Minh *et al*., 2014; Mermoz *et al*., 2015) varies between studies, determined by factors such as the local environmental conditions and equipment used (Santos *et al*., 2002; Mitchard *et al*., 2009; Lucas *et al*., 2010). Consequently, in order to reliably detect AGB change in dense, humid forests, where biomass density frequently reaches and exceeds 300 Mg ha^{-1} (Minh *et al*., 2014), P-band SAR – the longest wavelength of radar – may be the only effective option; this will become available after 2020, when the first satellite equipped with P-band sensors will be launched by the European Space Agency (Le Toan *et al*., 2011; ESA, 2015). Although L-band radar data appears to fulfil the requirements for this investigation, the potential situation of a small number of PAs within the humid forest biome (Ifon, Ohosu, Orle River and Udi) must be considered, as particularly high AGB levels within these PAs could limit the accuracy of Biomass Matching for detecting changes.

4.1.2 Estimation

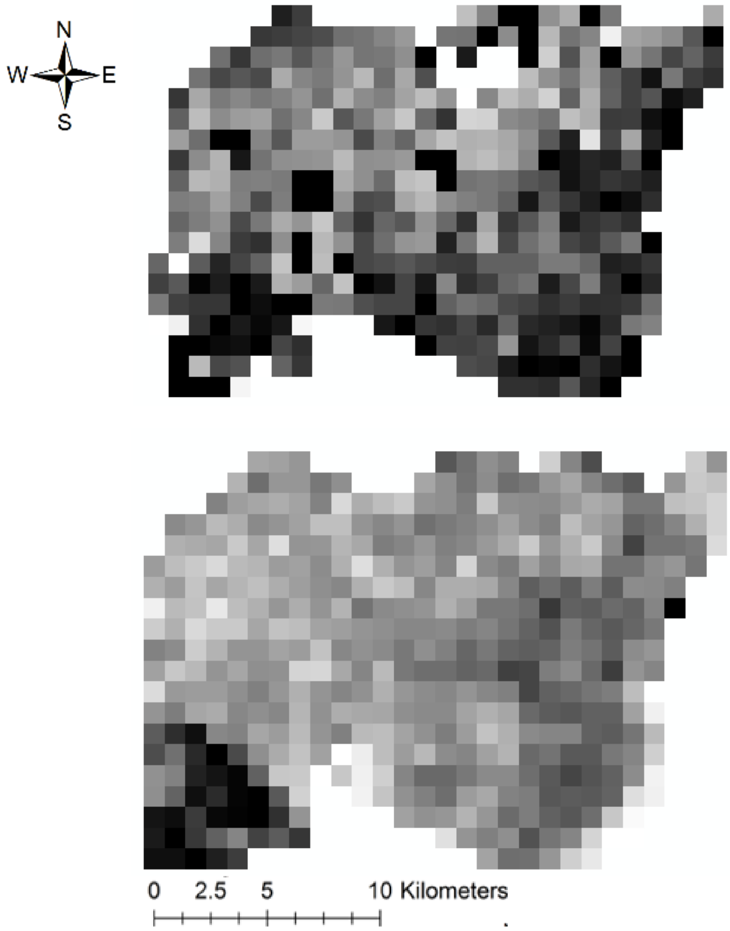


Fig. 4.1: Kamuku AGB at 1km Spatial Resolution. These have been derived from Avitabile *et al*. (2016)'s pan-tropical biomass map (above), and L-band RCS for the year 2010 (below). Lighter shades indicate higher pixel values for AGB (above) and RCS (below); for this PA, there is little correlation between the two.

As with AGB change detection, the ability of Biomass Matching to estimate change within PAs over time is heavily dependent on the data used, and in particular, the data from which the RCS-AGB relationship is derived. This is exemplified by the differences in AGB change between 2007 and 2017 (*Table 3.2*; *Fig. 3.4*) predicted when using the RCS-AGB relationship specific to this investigation, and that of Ryan *et al*. (2012) from their study of small-scale AGB change in Mozambican woodlands. Although the trends in mean AGB change are identical for each PA (*Fig. 3.4*), the RCS-AGB relationship of Ryan *et al*. (2012) consistently predicts higher AGB levels at each time point (*Fig. 3.4*), resulting in greater positive or negative AGB change being estimated for each study area between 2007 and 2017, with the exception of Lame-Burra (*Table 3.2*). These disparities are a product of the methods and data used to obtain each RCS-AGB relationship, as these determine the slope and y-intercept coefficients used to predict AGB density and change from SAR data. Ryan *et al*. (2012) regress the RCS of each radar scene in their investigation against field inventory data from 96 forest, woodland and cropland plots in the south of their study area between 2006 and 2009; from this, mean slope and y-intercept values (and thus a RCS-AGB relationship) could be obtained. Contrastingly, this investigation regressed the RCS of all PAs for the year 2010 against the AGB of all PAs derived from the pan-tropical AGB map of Avitabile *et al*. (2016). This data combines existing LIDAR-based tropical AGB maps (Saatchi *et al*., 2011; Baccini *et al*., 2012) with a high resolution reference dataset to give a fused AGB map 2000 – 2010 at 1km spatial resolution; while this circumvented the need for field data, inherent limitations with this method of obtaining a RCS-AGB relationship are apparent, including the low resolution of the AGB map (Avitabile *et al*., 2016) and potential dissimilarities between the RCS and reported AGB within certain PAs (*Fig. 4.1*). Although this may be a less robust method of obtaining a RCS-AGB relationship, it enabled development of one which was arguably more applicable to the PAs in this study than one such as Ryan *et al*. (2012)'s, a set of coefficients unique to that particular investigation. Furthermore, the general agreement and absence of statistically significant difference between the AGB changes over time estimated for each area by the two sets of coefficients ($t(38) = -1.110$, $p = 0.274$) suggests that both approaches may be a viable means of developing such relationships.

However, the accuracy of AGB change estimation by Biomass Matching is not only influenced by the RCS-AGB relationship employed, but also the SAR data itself. Indeed, though a strong relationship between L-band RCS and ecosystem AGB has frequently been reported (Mitchard *et al*., 2009; Mitchard *et al*., 2011; Ryan *et al*., 2012), interactions between the backscatter signal and vegetation structural properties which are uncorrelated with AGB prevents RCS from giving 'direct' measurements of AGB (Woodhouse *et al*., 2012). For example, while Mitchard *et al*. (2011) record a relationship of $R^2 = 0.86$ between L-band HV backscatter and AGB, this still indicates that 14% of the variance in AGB remains unaccounted for. Despite the increasing utility of remote sensing for informing estimates of ecosystem AGB and AGB change over large areas, the importance of robust field data in calibrating and validating estimates derived from remote sensing is often still advocated (Mitchard *et al*., 2014). Indeed, Mitchard *et al*. (2014) reveal considerable differences in regional AGB estimates across Amazonia between two remote sensing-derived pan-tropical maps (Saatchi *et al*., 2011; Baccini *et al*., 2012) and those obtained from a comprehensive field-based dataset. Therefore, although remote sensing applications like L-band SAR are becoming increasingly applicable for estimating ecosystem AGB change, associated limitations prevent such predictions from being wholly accurate; as such, Biomass Matching may be regarded as a useful tool for estimating relative AGB change within Nigerian PAs, thus providing a more general indication of their ability to protect habitats within their borders.

4.2 Habitat Conservation in Nigerian Dryland Protected Areas

Though the outcomes of statistical tests find no statistically significant difference between AGB change in protected and unprotected areas for any size category (*Fig. 3.5*) simple visual comparisons (*Table 3.4*) demonstrate that PAs in Nigerian drylands consistently experienced more positive AGB change than similarly-sized CAs between 2007 and 2017. From this, it could be inferred that PAs are generally more effective than CAs in Nigerian drylands for purposes of AGB and habitat conservation. Such results are supported by the findings of several studies comparing the effectiveness of savannah PAs to similar unprotected areas. In the Brazilian Cerrado, PAs are generally more effective than CAs at reducing habitat loss and conversion (Carranza *et al*., 2014; Paiva *et al*., 2015), while Ament and Cumming (2016) demonstrate natural cover loss in a small sample of South African PAs to be lower than that in matched CAs. The latter's results are particularly encouraging (Ament and Cumming, 2016): using similar methods, they find evidence to suggest that dryland PAs in another sub-Saharan African country are an effective means of protecting habitats from deforestation and degradation.

These positive findings are not restricted to dry forest and savannah ecosystems; studies of other tropical ecosystems repeatedly conclude that all forms of anthropogenic disturbance are lower in PAs compared to similar unprotected lands. Examples may be drawn from Costa Rica (Andam *et al*., 2008), the humid forests of central Africa (Bowker *et al*., 2017), the Ecuadorian

Andes (Cuenca *et al*., 2016), Mexico (Blackman *et al*., 2015) and across the pan-tropics as a whole (Nelson and Chomitz, 2011). Indeed, even those who suggest PA effectiveness has been overestimated (Sarathchandra *et al*., 2018) or find evidence for continuing forest loss within PAs (Gaveau *et al*., 2009), concede that PAs are still more effective than unprotected areas at reducing habitat loss and degradation. For instance, forest loss inside Sumatran PAs 1990-2000 occurred at a rate of 0.5% yr^{-1}, whereas that in unprotected areas was 4.1% yr^{-1} (Gaveau *et al*., 2009). Importantly, these decisions are also reached when using different types of data and different proxies for anthropogenic disturbance. These include inspections of optical remote sensing data for land-cover change (Beresford *et al*., 2013; Carranza *et al*., 2014; Ament and Cumming, 2016), fires as indicators of deforestation events (Nelson and Chomitz, 2011) and satellite deforestation data (Blackman *et al*., 2015; Bowker *et al*., 2017). The consistency of findings, even when such a wide range of data types are used, provides strong support for PAs being more effective than similar CAs at reducing AGB and habitat loss across the tropics.

4.2.2 Accuracy and Reliability of Findings

Although the results of this investigation reflect those of many similar studies, the accuracy and reliability of findings must first be assessed before definitive conclusions are drawn about Nigerian PA effectiveness. Firstly, the representativeness of this sample regarding Nigerian dryland PAs, and PAs in dry forest and savannah ecosystems more generally, is important to consider. While the original sample included 30 PAs broadly situated across the Guinea and Sudan Savannah biomes (*Fig 2.1*; *Fig 2.2*), 9 of these were forcibly excluded due to issues with subjecting them to Biomass Matching. Of these remaining 21 PAs, it is possible that four would fall into humid forest areas (*Fig 2.1*; *Fig 2.2*), leaving only 17 PAs to represent all those located within Nigerian savannahs. Additionally, the PAs included in this study were subjectively selected, largely according to the availability of key information on the WDPA; this inevitably resulted in a bias towards more strictly PAs for which more comprehensive information was available, particularly national parks. Though this could have exaggerated the effectiveness of this sample of PAs, the results of analyses regarding the relationship between protection levels and performance (*Fig. 3.9*) and suggestions that stricter protection does not always equate to better habitat conservation (Nelson and Chomitz, 2011; Pfeifer *et al*., 2012; Ferraro *et al*., 2013) would limit sample bias. Moreover, despite being small in size, high resolution, mesoscale studies may be an ideal means of investigating a spatially explicit occurrence such as AGB change, investigating PA effectiveness in specific countries or regions by using small samples (Curran *et al*., 2004; Carranza *et al*., 2014); large-scale studies with extensive samples (Nelson and Chomitz, 2011; Tranquilli *et al*., 2014; Bowker *et al*., 2017) may at times be too coarse to adequately investigate such phenomena (Ament and Cumming, 2016). Consequently, this small sample may be perfectly suitable for exploring and representing PA effectiveness in Nigerian dry forests and savannahs.

While the PA data may be adequate, the methods used to create CAs and thereby test the effectiveness of Nigerian PAs for AGB conservation must be scrutinised. 'Matching' methods use specialist software to generate any number of random control points in unprotected areas with similar characteristics to points in PAs; these are becoming increasingly popular in studies of PA effectiveness, owing to their objectivity, consideration of the non-random siting of PAs in landscapes, and ability to avoid bias from potential spillover effects (Andam *et al*., 2008; Gaveau *et al*., 2009; Joppa and Pfaff, 2010; Nelson and Chomitz, 2011; Carranza *et al*., 2014; Blackman *et al*., 2015; Bowker *et al*., 2017). Although this investigation employed an approach resembling matching methods, subjectively creating CAs is far less sophisticated, and consequently comes with potential limitations which could impact the aforementioned findings. The most detrimental would be the over-estimation of PA effectiveness: while size was considered during CA generation, other characteristics such as elevation and slope were only loosely accounted for; the overall similarities between PAs and their respectively-sized CAs may therefore have been limited, with CAs potentially possessing characteristics which would make them disproportionately more vulnerable to anthropogenic disturbance (Nelson and Chomitz, 2011; Beresford *et al*., 2013). Though this possible exaggeration of PA effectiveness would limit the investigation's utility to some extent, a 'subjective' matching method is arguably still more robust than simple comparisons of PAs to immediately adjacent unprotected areas (Pelkey *et al*., 2000; DeFries *et al*., 2005; Alo and Pontius Jr., 2008). These inside-outside comparisons fail to account for potential spillover effects (*Fig. 1.1*), the magnitude and direction of which differ greatly between PAs (Pfaff and Robalino, 2012); while not always present (Andam *et al*., 2008; Gaveau *et al*., 2009; Carranza *et al*., 2014), when leakage does occur, it can significantly impact inferences of PA effectiveness if these surrounding areas are used as the controls. For example, Ament and Cumming (2016)'s study of South African national parks found negative spillover effects to extend up to 50km from five different PA boundaries, while positive effects were evident for another 14, and in some cases extended over 50km from their borders. Despite its relative simplicity, subjectively generating CAs improves the chances of these effects being avoided, thereby limiting the potential for significant over- or under-estimations of PA effectiveness.

Although the collection methods may be relatively robust, characteristics of the dataset itself may have restricted analytical rigour, and assumptions pertaining to the causes of AGB change could impact the validity of conclusions about PA effectiveness. While more focused studies can be beneficial in assessments of PA performance (Ament and Cumming, 2016), the small sample sizes of PAs and CAs (21 and 12 respectively) limited the utility of tests for statistically significant difference between their mean AGB change values. As such, simple

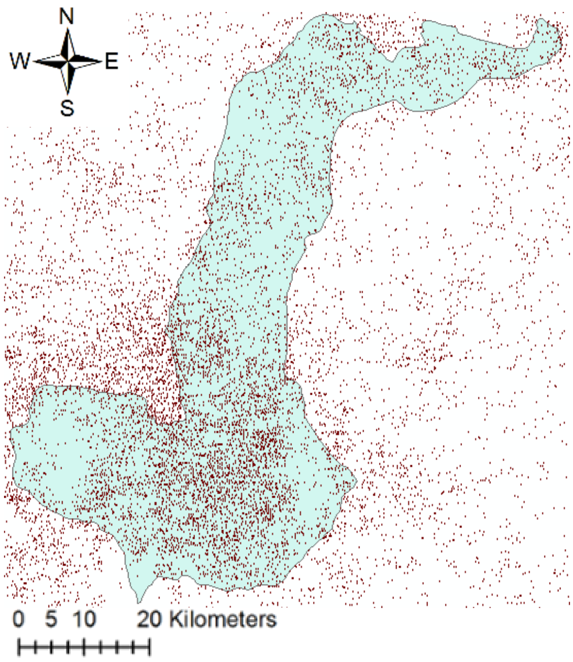


Fig. 4.2: Fire in Nigerian Dryland PAs. The light blue shapefile delimits the area of Upper Ogun/Old Oyo – each red point inside and outside its borders represents a fire detected by the MCD14DL sensor for the year 2017.

descriptive comparisons were far more useful, revealing that PAs of all size classes (and overall) performed better than similar CAs (*Table 3.3*). It must be noted, however, that these size classes used to subdivide PAs and guide CA creation were subjectively established; there is no universally-accepted method of doing this (Maiorano *et al*., 2008), so its potential impact on the results (*Table 3.3*) and subsequent conclusions must be considered. The greatest influence on conclusions of PA effectiveness may however stem from the assumptions of what drives AGB change within dry forest and savannah PAs and CAs. AGB increases are most likely the product of successful conservation efforts, but losses can result from a number of root causes, including both natural and unnatural fires. These are ubiquitous in dryland areas and essential for maintaining dry forests and savannahs as alternative stable states (Van Langevelde *et al*., 2003; Staver *et al*., 2011a; Staver *et al*., 2011b; Hoffman *et al*., 2012). Indeed MODIS data of fires in Nigeria between 2007 and 2017 (available at: https://earthdata.nasa.gov/firms) emphasises the frequency with which fires occur, even within the boundaries of PAs (*Fig. 4.2*). Although fires can be purposefully ignited to facilitate clearance for agriculture (Frost, 1999; Nelson and Chomitz, 2011; Archibald *et al*., 2012), those within tropical dryland PAs are just as likely due to lightning strikes or controlled burns by park managers (Bond and Archibald, 2003). The source of fires cannot be determined by MODIS remote sensing data, but if a large proportion of AGB losses 2007-2017 within a PA resulted from either naturally-induced or controlled fires, its conservation effectiveness would be underestimated by Biomass Matching. The potentially significant impact of fires on AGB change in dryland PAs must therefore be considered when making inferences about their effectiveness.

Overall, PAs in Nigerian drylands are generally more effective at conserving and enhancing AGB levels than ‘similar’ unprotected CAs. While the potential influence of the aforementioned limitations and assumptions on the results must be considered, the support from findings of numerous comparable studies across the tropics (Andam *et al*., 2008; Gaveau *et al*., 2009; Joppa and Pfaff, 2010; Nelson and Chomitz, 2011; Beresford *et al*., 2013; Carranza *et al*., 2014; Paiva *et al*., 2015; Blackman *et al*., 2015; Ament and Cumming, 2016; Cuenca *et al*., 2016; Bowker *et al*., 2017; Sarathchandra *et al*., 2018) gives credence to this argument. Therefore, it can be concluded with some confidence that in Nigerian dry forests and savannahs, PAs offer an effective means of protecting natural habitats from anthropogenic disturbances.

4.3 Factors Influencing Protected Area Effectiveness in Nigerian Drylands

Understanding the extent to which different factors drive PA performance is incredibly important. Inferences can be made as to why existing PAs are particularly effective or ineffective in terms of habitat conservation, informing attempts to maintain or improve their performance, and it can assist in the establishment of PAs by ensuring that newly gazetted areas possess characteristics which will maximise their effectiveness. However, discussions surrounding the characteristics and environmental variables influencing PA effectiveness in terrestrial ecosystems are incredibly complex: not only can the relative importance of factors vary between countries, regions and biomes, but interactions between them can make it difficult to isolate their individual effects. Regardless of such difficulties, attempts will be made to determine which factor(s) may be most important in driving PA performance in Nigerian dry forests and savannahs, as findings could play a role in influencing regional and national conservation policies.

4.3.1 Accessibility

Disentangling the effect of accessibility on PA effectiveness is complicated by how different studies consider it as the product of different combinations of environmental variables (Joppa and Pfaff, 2009; Nelson and Chomitz, 2011; Pfaff *et al*., 2014; Bowker *et al*., 2017 Beresford *et al*., 2018); despite this, however, it is frequently found to substantially influence PA performance. Slope steepness is a crucial factor determining PA accessibility, and in this investigation, ‘Accessibility – Slope’ was found to contribute considerably to PA effectiveness (*Table 3.5*; *Fig. 3.11*). These results imply that inaccessible PAs, particularly those characterised by steep slopes and undulating terrain, will offer far more effective habitat conservation, an observation supported by a number of similar studies (Joppa and Pfaff, 2009; Pfaff *et al*., 2014; Bowker *et al*., 2017;

Beresford *et al*., 2018). While it is somewhat surprising that mean elevation, proximity to major roads, and proximity to major settlements are responsible for so little of the variation in AGB change (*Table 3.5*), there a various potential explanation for this. Although higher values of these environmental variables are more commonly associated with greater PA effectiveness (i.e. higher elevation, and greater distance to major settlements and roads), this does not always hold true (Joppa and Pfaff, 2009); for example, a PA may still perform well even if situated at low altitude and surrounded by human infrastructure. The small sample size of this investigation would increase the likelihood of such incidences having a notable effect on the associated regressions. Furthermore, the lack of perceived influence of a PA's proximity to major settlements and roads on its effectiveness could originate from the novel buffering approach employed (see section 2.9.4); studies which use alternative methods, such as Euclidean distance measures (Nelson and Chomitz, 2011; Bowker *et al*., 2017), find proximity to settlements and road networks to contribute notably to PA accessibility, and subsequently to PA effectiveness. Therefore, Nigerian dryland PAs appear to broadly support the notion that inaccessible PAs are more effective: more remote areas are less susceptible to adverse anthropogenic activities and so less likely to experience habitat loss and conversion, rendering them more effective for conservation purposes.

As accessibility is often so prominent in discussions of PAs effectiveness, it is unsurprising that it is argued to interact strongly with other factors influencing performance. The level of protection a PA receives may be inherently dictated by its accessibility, and indeed historically, more strictly PAs have been preferentially situated in more remote areas (Scott *et al*., 2001; Peres and Lake, 2003; Hoekstra *et al*., 2005; Joppa and Pfaff, 2009). Early PAs, such as Yosemite and Yellowstone national parks, were gazetted in lands which, though prized for their natural beauty and rare species, were also perceived to be inaccessible and of little economic interest (Scott, 1999; Phillips, 2004); this legacy of particularly reputable PAs, such as strict nature reserves and national parks, being sited on marginal lands (Joppa and Pfaff, 2009) may overwhelming explain why such areas often provide such effective habitat protection. In Nigeria, Gashaka-Gumti National Park may exemplify this: between 2007 and 2017, it experienced the second highest per hectare AGB increase (+3.44), while possessing some of the steepest slopes (11.98º) and being at the highest altitude (739.45m a.s.l) of all the PAs studied. Furthermore, more remote PAs are arguably also less vulnerable to PADDD, particularly those isolated from major road networks. When this is true, PAs are far less viable for major infrastructural projects and resource extraction (Bernard *et al*., 2014; Symes *et al*., 2016); minimal economic incentives mean that national and regional authorities will be less inclined to permit detrimental practices, ensuring that PAs remain effective. The influence of accessibility on a PA's level of protection through both non-random siting (Joppa and Pfaff, 2009) and propensity for PADDD (Symes *et al*., 2016), emphasises the significance of this factor in determining PA performance.

4.3.2 Level of Protection

The nationally-implemented – and thus internationally-recognised (Juffe-Bignoli *et al*., 2014) – level of protection a PA receives can be influential in dictating its overall conservation effectiveness. Various studies of PAs in both tropical drylands (Carranza *et al*., 2014; Francoso *et al*., 2015) and humid forests (Scharlemann *et al*., 2010; Pfeifer *et al*., 2012; Nolte *et al*., 2013) argue that stricter protection results in greater PA effectiveness; the national parks (IUCN II) in this sample of PAs – Gashaka-Gumti, Kainji Lake, Kamuku, Upper Ogun and Yankari – certainly support this notion, as they all experienced distinctly positive AGB change (*Table 3.3*) between 2007 and 2017. However, on average this increase is lower than in IUCN IV PAs (*Fig. 3.9*b), and indeed, there are those who argue that more mixed-use PAs can be equally, if not more, effective for habitat conservation than strict PAs (Nelson and Chomitz, 2011; Andrade and Rhodes, 2012; Porter-Bolland *et al*., 2012; Sassen *et al*., 2013; Pfaff *et al*., 2014; Blackman, 2015; Blackman *et al*., 2015). There are also those who argue that level of protection has no discernible impact on PA performance (Nagrenda, 2008), a stance somewhat supported by the 'IUCN Categories' categorisation used here (*Fig. 3.9*a). The conflicting nature of findings alludes to considerable complexities associated with this debate, and suggests that the direction of the relationship between protection and PA performance may ultimately depend on its interaction with additional factors.

Consistent with earlier discussions, accessibility can be essential in determining whether more or less strict protection is inevitably more effective for an area, but this can often be contingent on the measures used to determine PA effectiveness. Performance can be a function of absolute AGB change within a PA – an approach employed in this investigation and by others (Carranza *et al*., 2014; Bowker *et al*., 2017) – or of avoided AGB or habitat loss; in other words, the amount of potential loss prevented by a PA's presence (Nolte *et al*., 2013; Pfaff *et al*., 2014). When viewed in relation to absolute change, stricter PAs will often be more effective, owing to their situation on more marginal land (Joppa and Pfaff, 2009) where the potential for anthropogenic disturbance is unlikely. Conversely, mixed-use PAs usually perform better in terms of avoided AGB loss, as they are disproportionately established in accessible, high-pressure areas where the potential for reducing habitat loss is far greater (Nelson and Chomitz, 2011; Nolte *et al*., 2013; Pfaff *et al*., 2014). However, such trends do not hold true for this investigation or a number of others (e.g. Porter-Bolland *et al*., 2012), where PAs classified as 'mixed-use' experienced higher AGB change in absolute terms than stricter PAs (*Fig. 3.9*). It is therefore possible that further intricacies may be associated with the levels of protection afforded to PAs, running deeper than their overarching classifications.

While nationally- and internationally-designated levels of protection are undoubtedly important to PA effectiveness, smaller scale variations in management and resourcing can be equally influential, often circumventing the methods of higher institutions (Bowker *et al*., 2017). Indeed, the importance of appropriate management and resourcing to PA effectiveness has been repeatedly emphasised (Leverington *et al*., 2010; Andrade and Rhodes, 2012; Laurance *et al*., 2012; Sassen *et al*., 2013; Tranquilli *et al*., 2014; Watson *et al*., 2014; Blackman *et al*., 2015), and the suitability of practices can vary considerably depending on location. In high-pressure regions, less strictly PAs can be a very practical and rewarding option, particularly in countries where PA funding might be limited; this is true of many West African nations, where political instability often results in low budgets for PA management (Struhsaker *et al*., 2005; Jachmann, 2008). Allowing low-level habitation and sustainable use of PA resources by local and indigenous communities can prevent conflicts from arising between these peoples and PA administration, as well as encouraging local participation in management and resourcing, especially when community livelihoods depend on a PA remaining intact (Andrade and Rhodes, 2012; Sassen *et al*., 2013; Blackman, 2015). These collaborative management agreements between PA authorities and local people can aid forest protection and recovery (Sassen *et al*., 2013) and greatly reduce maintenance and monitoring costs (Andrade and Rhodes, 2012) to ensure long-term PA viability. Such approaches may somewhat explain the observed relationship between level of protection and effectiveness for Nigerian dryland PAs: less strictly PAs with more flexible management strategies on average experienced greater AGB increase between 2007 and 2017 than their more strictly protected counterparts (*Fig. 3.5*). However, the performance of mixed-use PAs is highly variable and heavily dependent on concessions offered to local communities (Blackman, 2015); occasionally, these approaches may not satisfy the requirements of local people, leading instead to unsustainable levels of encroachment and resource exploitation (Francoso *et al*., 2015). In these circumstances, strictly PAs which are rigorously managed and afforded ample resources are far more likely to be effective (Pfeifer *et al*., 2012; Francoso *et al*., 2015). Variability in management requirements are exemplified by Mt Elgon Forest Reserve/National Park in Uganda, where changing contexts over time – such as fluctuating coffee prices and population densities – have dictated whether strict law enforcement or collaborative forest management are more effective for maintaining forest cover within different sectors of the park (Sassen *et al*., 2013). Management and resourcing requirements for PAs differ both spatially (within and between PAs) and temporally, with pronounced implications for PA effectiveness.

4.3.3 <u>Size</u>

Although there is no clear-cut relationship between PA size and performance in Nigerian drylands (*Fig. 3.7*) , there is a general consensus that larger PAs offer more effective habitat conservation across the globe, supported by findings from such disparate regions as central Africa (Tranquilli *et al*., 2014; Bowker *et al*., 2017), Canada (Leroux and Kerr, 2013) and Italy (Maiorano *et al*., 2008). While interactions with additional factors are likely to be important, size alone may independently account for this positive relationship with PA performance on many occasions. A prominent argument is that large PAs have their own ‘identity’ (Maiorano *et al*., 2008): they possess environmental characteristics which differentiate them from their surrounding landscapes, and are often encompassed by sizeable ‘buffer’ zones, where the positive spillover of PA effects (e.g. Ament and Cumming, 2016) provides an extra line-of-defence against anthropogenic disturbances (DeFries *et al*., 2005; Blackman *et al*., 2015). Meanwhile, small PAs often lack such buffers, and are more likely to be component parts of larger-scale ecosystems outside their borders, leaving them more vulnerable to the influences of land-cover change in these areas (Hansen and DeFries, 2007; Pfeifer *et al*., 2012; Clark *et al*., 2013). As well as experiencing less absolute habitat change, large PAs may also perform better in relative terms. Longer boundaries in relation to their surface area mean that, even if some disturbance leaks across their borders, the majority of the PA will remain untouched (Leroux and Kerr, 2013). As a result, larger PAs will usually experience proportionally less degradation (Clark *et al*., 2013); therefore, even if more AGB loss occurs within a large PA than a smaller PA overall, the distribution of this loss over a wider area means that Mg ha^{-1} AGB loss will be lower within the large PA. With such strong support for larger PAs offering more effective conservation, is it somewhat surprising that a more positive relationship between size and AGB change is not observed for this investigation.

Interactions with additional factors may explain why there is little connection between size and PA effectiveness in Nigerian drylands. Accessibility may play a key role in influencing the direction of this relationship; however, evidence suggests that this will merely reinforce the existence of a positive relationship between size and effectiveness. Similar to more strictly PAs (Joppa and Pfaff, 2009), large PAs may also be preferentially situated in remote areas (McKinney, 2005; Leroux and Kerr, 2013; Bowker *et al*., 2017) characterised by low population densities, leaving them less vulnerable to local disturbances such as agricultural conversion and resource extraction (Struhsaker *et al*., 2005). This may subsequently link to the high levels of protection large PAs often receive, and initiate something of a positive feedback loop. Their size and advantageous location within landscapes may attract more generous resourcing from governments and NGOs (Struhsaker *et al*., 2005; Blackman *et al*., 2015), facilitating sound management practices and appropriate law enforcement to ensure long-term viability and effective habitat conservation (Leverington *et al*., 2010; Andrade and Rhodes, 2012; Laurance *et al*., 2012; Sassen *et al*., 2013; Tranquilli *et al*., 2014; Watson *et al*., 2014), which, in turn, will encourage further resourcing. Therefore, it is difficult to ascertain why large PAs in Nigerian drylands are not notably more effective than smaller PAs, as the results displayed here are certainly somewhat anomalous in the context of previous, similar investigations.

4.3.4 Age

There is debate as to whether older (Eagles *et al*., 2002; Dudley *et al*., 2007; Andrade and Rhodes, 2012) or younger PAs (Rao *et al*., 2002; Blackman *et al*., 2015; Bowker *et al*., 2017) might offer better habitat protection, but in Nigerian drylands increasing age results in increased PA effectiveness (*Fig. 3.8*), with a subtle relationship apparent between the two variables. As age is an abstract characteristic, any influence on PA performance will only result from interactions with other factors, though this may almost exclusively relate to level of protection, and specifically, management and resourcing. Over time, PA administration in both strictly monitored and mixed-use areas may naturally improve (Eagles *et al*., 2002; Dudley *et al*., 2007); in the former, this may stem from greater resourcing stimulated by enhanced reputation and global interest, whereas the latter may benefit from increased community compliance with regulations (Andrade and Rhodes, 2012). Alternatively, it is also possible that younger tropical PAs, established post-colonially, will receive more enthusiastic support from both national governments and local communities (Blackman *et al*., 2015), rendering them less vulnerable to disturbance (Rao *et al*., 2002) or from PADDD (Symes *et al*., 2016). This may even be particularly applicable to tropical Africa (Bowker *et al*., 2017), where many countries were still recently subjected to colonial rule (Babou, 2010). However, as none of the PAs included in this investigation were established until after Nigeria gained independence in 1960 (Encyclopaedia Britannica, 2019) such an argument would be invalid, and thus potentially explain the positive relationship between PA age and performance in Nigerian drylands.

4.3.5 Summary

When assessing the relative importance of different factors in driving PA effectiveness in Nigerian drylands and at broader scales, it must be considered how each characteristic affects PA performance both independently and through interactions with others. While the type of protection a PA receives, particularly with regards to its management and resourcing, is a commonly recurring theme in debates (Leverington *et al*., 2010; Andrade and Rhodes, 2012; Laurance *et al*., 2012; Sassen *et al*., 2013; Tranquilli *et al*., 2014; Watson *et al*., 2014; Blackman *et al*., 2015), disagreement persists as to whether strict protection (Pfeifer *et al*., 2012; Francoso *et al*., 2015) or mixed-use approaches (Andrade and Rhodes, 2012; Sassen *et al*., 2013; Blackman, 2015) exert a more positive influence on effectiveness. On the other hand, a clear trend exists between accessibility and PA performance, with more remote areas almost always offering better opportunities for habitat conservation (Joppa and Pfaff, 2009; Nelson and Chomitz, 2011; Pfaff *et al*., 2014; Bowker *et al*., 2017 Beresford *et al*., 2018). Combine this with its key interactions with other factors, particularly level of protection (Joppa and Pfaff, 2009), and it could be argued that accessibility is the most important determinant of PA performance in the dry forests and savannahs of Nigeria.

4.3.6 Potential limitations

The WDPA was an invaluable resource for this investigation, providing information regarding particular PA characteristics, as well as downloadable shapefiles which were integral to all parts of the analysis; however, at times there were issues with this data. Some such problems could be rectified: the large inaccuracies with reported PA sizes could be avoided by instead using MATLAB R2017*a* to manually calculate the spatial extent of each, and if a PA's 'Status Year' was not given by the WDPA, this could be roughly estimated by reference to less verified sources (e.g. Parks.it, 2018). Unfortunately, some problems were irresolvable, with perhaps the most important being the spatial inaccuracies often associated with the PA shapefiles, an issue also recognised by previous studies (Nagrenda *et al*., 2013). Considerable complications could arise if these inaccuracies were sufficiently large, affecting a PA's mean elevation and slope values – crucial variables associated with accessibility – and its calculated size, all of which could influence the observed relationships

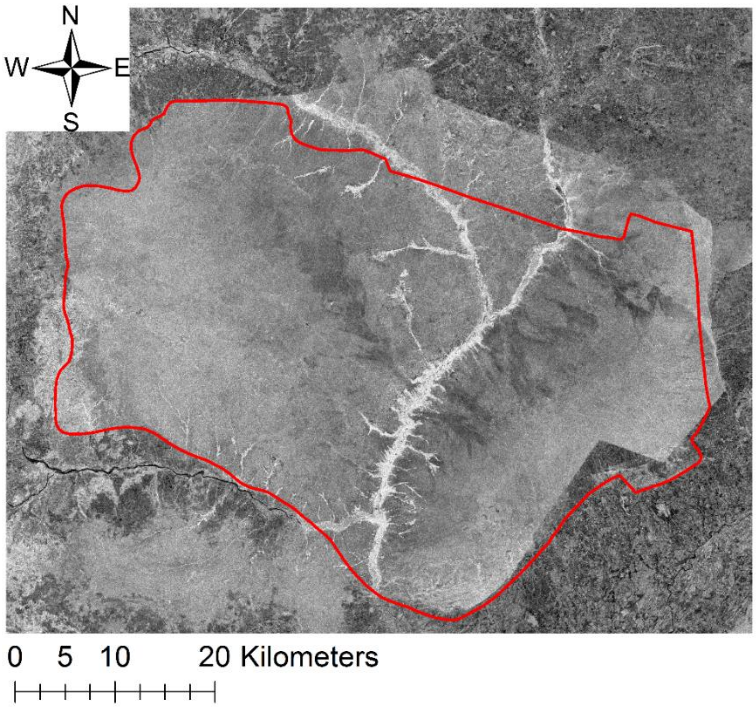


Fig. 4.3: Spatial Inaccuracies with WDPA Shapefiles. The outline of the shapefile for Yankari National Park (in red) overlies 2017 L-band SAR data, where lighter shades reflect higher values and therefore indicate the PA's extent. Clear inaccuracies with the shapefile are visible, both where lands outside the PA have been included within it, and areas inside which have been excluded.

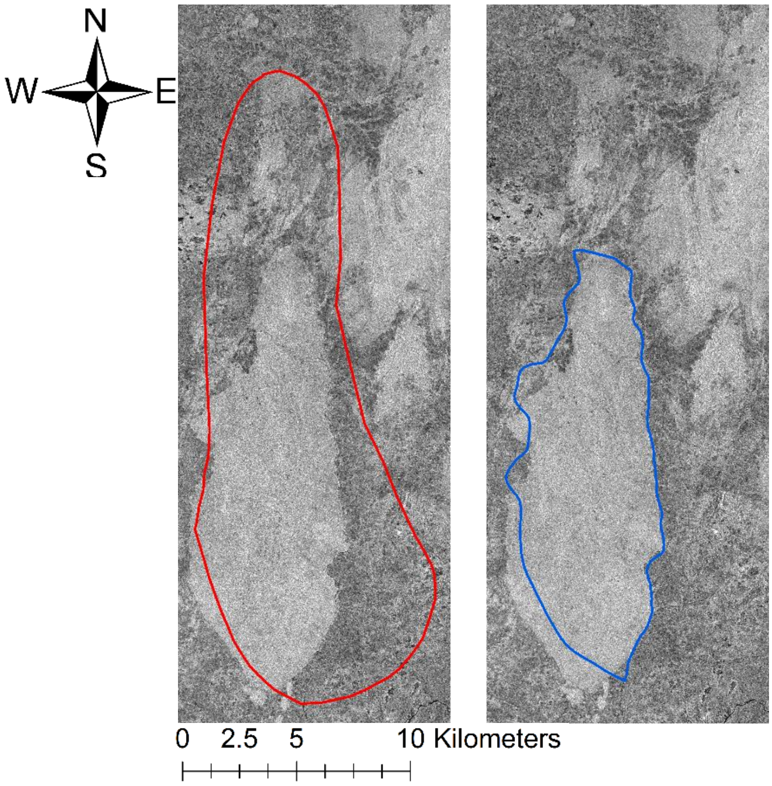


Fig. 4.4: Multiple PA Shapefiles. The outlines of the two shapefiles available for Alawa, overlying 2017 L-band SAR data, where lighter pixels indicate the PA's approximate extent. The red shapefile (left) is highly inaccurate, whereas that in blue (right) – though imperfect – follows the PA's boundaries far more closely.

with AGB change for the sample of Nigerian PAs. An even more pertinent issue could be the potential impact of such spatial errors on perceived PA effectiveness: if adjacent, unprotected lands which had experienced disturbance 2007 – 2017 were wrongly included within a shapefile's area, this would underestimate the effectiveness of the PA in question. The opposite would be true if such areas had instead experienced AGB increases during the course of the study period. Indeed, this is exemplified by Yankari National Park, where the shapefile provided by the WDPA does not adequately reflect the PA's boundaries (*Fig. 4.3*). Furthermore, certain PAs were represented by two different shapefiles, sometimes varying considerably in terms of shape and size. For some, the 'correct' shapefile was easy to ascertain (*Fig. 4.4*), whereas for others this was far more challenging. These inherent shortcomings with the WDPA shapefiles could extend to multiple parts of the investigation, highlighting the disadvantages of relying on a single source for such important data.

In addition to the potential limitations with the WDPA dataset, there were spatial inaccuracies associated with the city centroid (CIESIN, 2017) and road network (CIESIN, 2013) data used to measure the proximity of each PA to major settlements and roads in Nigeria. For the settlement data, the locations of cities were depicted by individual pixels, the precision and accuracy of which were wholly dependent on the size of input areal units (CIESIN, 2017), while for the road data, horizontal accuracy could be anywhere between 30-500m (CIESIN, 2013). This could have altered both the number of settlements and length of road found within a PA and its associated 15km buffer. Furthermore, though populations of city centroids were largely derived from the 2010 round of national censuses collected between 2005 and 2014, in some circumstances contemporary data was unavailable, forcing older estimates to be used or figures to be extrapolated (CIESIN, 2017). As, for the purposes of this investigation, major settlements were classed as those with populations exceeding 50,000 in 2010, any outdated information could influence the number of city centroids included in the analysis, and hence the number of settlements located within PAs and their associated buffers. These limitations could have affected the extent to which these two variables were perceived to interact with PA AGB change (*Fig. 3.12*; *Fig. 3.13*).

Although spatial inaccuracies may partially account for the limited relationships observed between AGB change and PA proximity to major settlements and roads, the novel buffering approach (see section 2.9.4) may provide a better explanation. Unlike the Euclidean distance measures of previous studies (Nelson and Chomitz, 2011; Bowker *et al*., 2017), standardised buffers of 15km were placed around all PAs; all settlements and roads within PAs and their associated buffers were deemed to have easy access to the PA, so the number of city centroids and length of road contained within each of these was recorded. As well as rendering the resultant data less comparable to the findings of others (Nelson and Chomitz, 2011; Bowker *et al*., 2017), the buffer extents were subjectively established. This presented its own issues: accessibility measures were heavily founded on the distances local communities in sub-Saharan Africa are willing to travel for key resources, especially fuelwood (Wessels *et al*., 2013); the '15km' value was derived from the study of an urban area in Botswana, which found that most residents would travel no further than 15km for fuelwood (Hiemstra-van der Hoorst and Hovorka, 2009). This arbitrary figure could easily be less (some argue local disturbance will rarely extend 1.5km beyond an urban area (Wessels *et al*., 2013)) or more (dedicated fuelwood suppliers would likely be willing to travel further (Matsika *et al*., 2013)), but using travel distances for fuelwood as a proxy for accessibility may be particularly applicable to Nigeria. An outdated energy infrastructure means that 95% of households still use biomass as their primary energy source (UNDP, 2016), but the generally poor condition of many rural road networks (Akinwale, 2010; Idris and Salisu, 2016) will limit the distances people are able to travel for extraction. Therefore, while unsustainable fuelwood practices (Matsika *et al*., 2013) are an important form of disturbance, poor rural infrastructure (Akinwale, 2010; Idris and Salisu, 2016) may render fuelwood in PAs largely inaccessible to all but the most local rural dwellers; as such, 15km may be a reasonable size for PA buffers. The buffer extents can therefore be justified to some degree, but the approach itself may still be largely responsible for the lack of relationships between PA effectiveness and proximity to major settlements and roads. Consequently, mean elevation and slope may provide a far better indication of PA accessibility in this investigation.

Methodological design may also have affected how a PA's level of protection was perceived to influence its performance. The results here suggest that less strictly PAs are more effective in conservation terms (*Fig. 3.9*), but the categorisations applied were guided by the approaches of previous studies (Scharlemann *et al*., 2010; Nelson and Chomitz, 2011; Pfeifer *et al*., 2012; Nolte *et al*., 2013; Carranza *et al*., 2014; Blackman *et al*., 2015) and so ultimately subjective in nature. This is particularly true of the 'Strict Protection/Mixed-use' grouping (*Fig. 3.9*a), as the category PAs are designated to often differs between studies: some consider IUCN I – IV to be 'strict' and IUCN V – VI to be 'mixed-use' (Nelson and Chomitz, 2011; Carranza *et al*., 2014; Blackman *et al*., 2015), others believe IUCN I and II to be stricter and III – VI to be less restrictive (Scharlemann *et al*., 2010), and there are those who employ more graded groupings uninformed by IUCN classifications (Pfeifer *et al*., 2012; Nolte *et al*., 2013). As there is no universal criteria when it comes to grouping PAs into 'strict' and 'mixed-use' protection, it should be considered how the categorisations applied in both this investigation and others might have influenced conclusions about the effect of different levels of protection on PA performance. For example, in this study, if IUCN IV PAs had been included in the 'Strict Protection' category, more strictly PAs would have experienced more positive AGB change than those which classed as 'Mixed-use' (*Fig. 3.9*a). Therefore, considering management stringency in terms of IUCN classification (*Fig. 3.9*b) is the more reliable approach, as though imperfect (Burgess *et al*., 2005; Leroux *et al*., 2010), it more objectively represents the level of protection received by different PAs.

While there are limitations associated with the factors included in the analysis for research question 3, the exclusion of potentially significant factors should also be considered. Indeed, the four factors considered to impact PA effectiveness in Nigerian drylands were selected according to their perceived importance in the literature and relative ease of measurement (Maiorano *et al*., 2008; Joppa and Pfaff, 2009; Scharlemann *et al*., 2010; Nelson and Chomitz, 2011; Blackman *et al*., 2015; Bowker *et al*., 2017). Other studies of PA performance incorporate more, some of which can be difficult to quantify. Perhaps the best example of this is the management and resourcing received by PAs (Leverington *et al*., 2010; Andrade and Rhodes, 2012; Laurance *et al*., 2012; Sassen *et al*., 2013; Tranquilli *et al*., 2014; Watson *et al*., 2014; Blackman *et al*., 2015). While this was considered in terms of its interactions with other factors, the sheer number of quantitative and qualitative variables involved rendered it far too complex for this investigation to assess independently of other characteristics. For example, Leverington *et al*. (2010) list of host of potential indicators, and while some of these are quantifiable, many more – including adequacy of staff training, adequacy of law enforcement and maintenance of equipment – are inherently subjective and complex in nature, requiring extensive knowledge which was beyond the scope of this study. Indeed, this factor emphasises the intricacies involved in debates of PA effectiveness, and the difficulties in ascertaining which might exert the greatest influence on their performance in Nigerian drylands.

4.4 Case study: Habitat disturbance in Taraba State, Nigeria

	Size (ha)	**Mean Elevation (m a.s.l)**	**Mean Slope (°)**	**AGB change (Mg ha^{-1})**
Gashaka-Gumti	608,410	739.45	11.98	+3.44
Control Area 1	618,090	654.93	12.07	+3.55
Control Area 2	640,120	164.91	1.77	-1.27

Table 4.1: Research Question 4 – Key Characteristics of Areas; while Gashaka-Gumti and CA 1 are noticeably very similar in all aspects, CA 2 is clearly situated in a more lowland area.

To determine the effectiveness of Biomass Matching at detecting (and estimating) incidences of known disturbance, and to assess the contribution of PAs in Taraba State to habitat conservation, AGB change maps for Gashaka-Gumti, and 'very large' CAs 1 and 2 were compared (*Fig. 4.5*), along with the estimated AGB change 2007 – 2017 to have occurred in each (*Fig. 4.6*). While both CAs are a similar size to Gashaka-Gumti, only CA 1 is also characterised by high elevation and steep slopes; CA 2 is far more topographically accessible, encompassing lowland areas with far gentler slopes (*Table 4.1*).

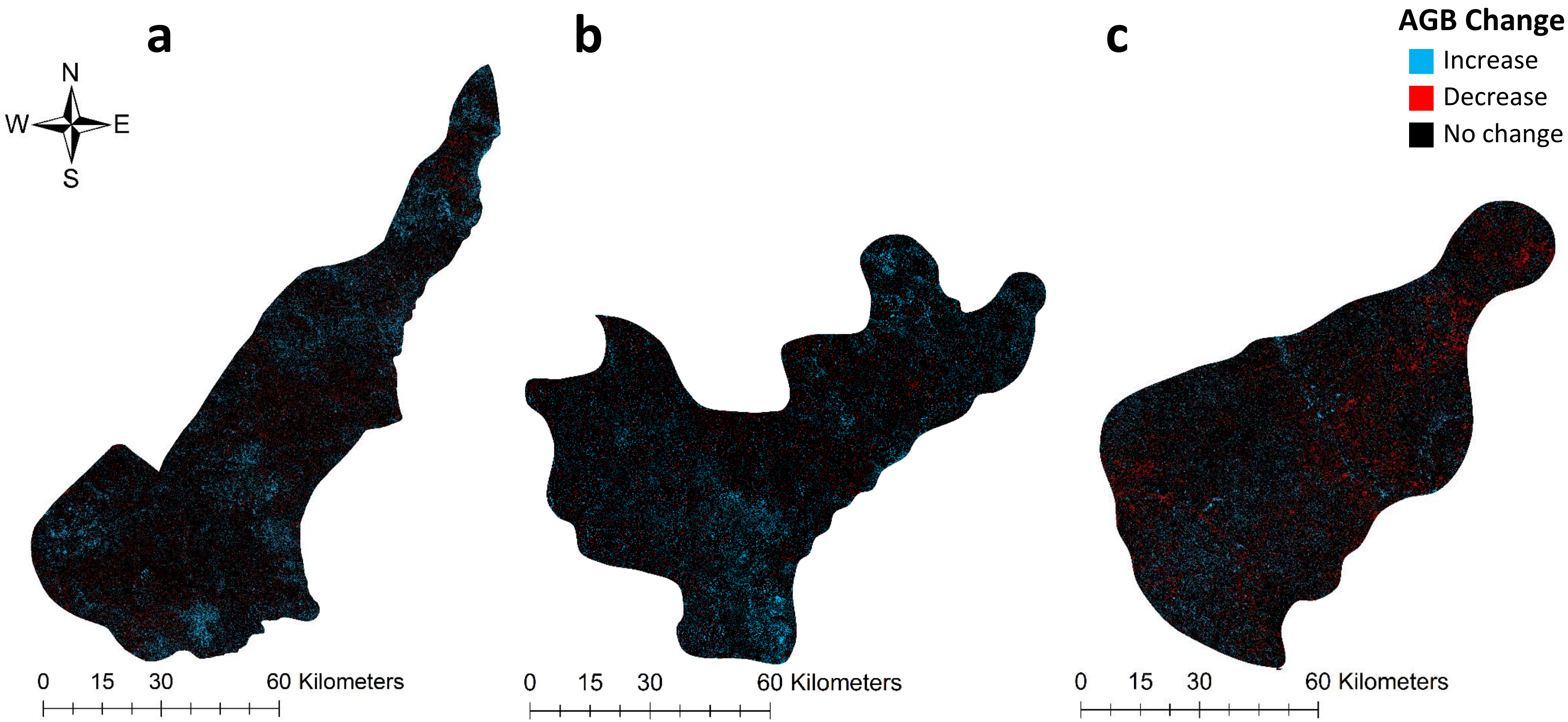


Fig. 4.5: AGB Change Maps for a) Gashaka-Gumti, b) (Very large) Control area 1, and c) (Very large) Control area 2.

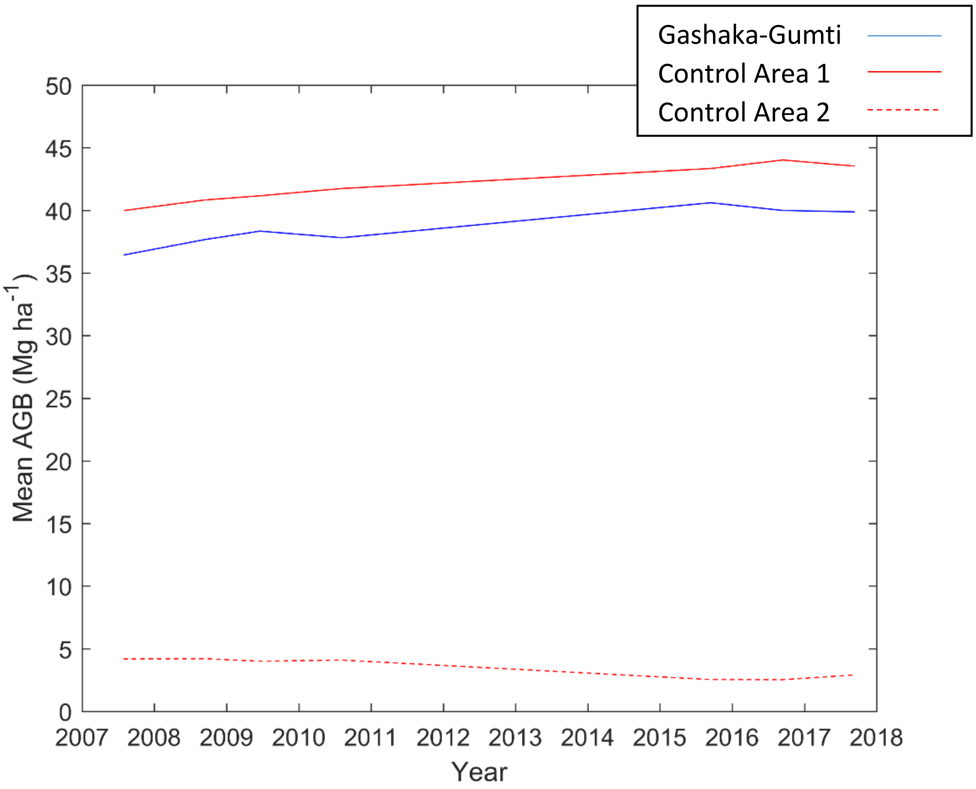


Fig. 4.6: Mean AGB Change 2007-2017 for Gashaka-Gumti, (Very large) Control Area 1 and (Very large) Control Area 2.

4.4.1 Woodland Clearance in Taraba State – verification by Biomass Matching

Recent, alarming rates of woodland clearance in Taraba State, a savannah region of eastern Nigeria, have been reported by a variety of a variety of authors (Ahmed *et al*., 2016; Aiytan, 2016; Chapman, 2016; Ahmed and Oruonye, 2017), but there has been little attempt to validate or quantify the actual extent of this disturbance. Biomass Matching, using L-band SAR data, may provide a means of resolving this issue, so as part of this investigation, three sizeable areas within Taraba State were subjected to the procedure: Gashaka-Gumti National Park, and 'very large' CAs 1 and 2. While both Gashaka-Gumti and CA 1 were characterised by high altitudes and steep slopes, land within CA 2 was far more topographically accessible (*Table 3.6*), and thus potentially more vulnerable to anthropogenic disturbance (Joppa and Pfaff, 2009). Therefore, CA 2 would arguably be the most useful in any efforts to validate accounts of extensive woodland clearance in the state (Ahmed *et al*., 2016; Aiyetan, 2016; Chapman, 2016; Ahmed and Oruonye, 2017), particularly as even subtle AGB changes in tropical drylands can be effectively detected by L-band radar (Mitchard *et al*., 2011; Ryan *et al*., 2012).

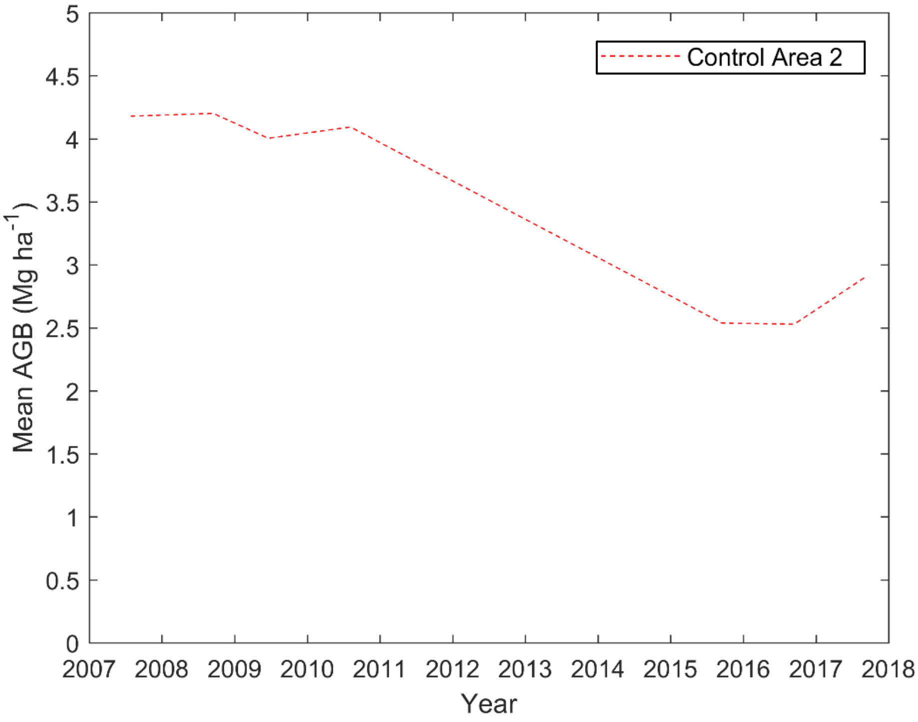


Fig. 4.7: Mean AGB Change 2007-2017 for (Very large) Control Area 2. This has been displayed alone to emphasise the recent decline in AGB.

The outputs of Biomass Matching for CA 2 certainly support the growing body of evidence documenting the denudation of large swathes of West Africa's savannah woodlands (Franck and Hansen, 2014; CITES, 2015; Ahmed *et al*., 2016; Aiyetan, 2016; Chapman, 2016; Ahmed and Oruonye, 2017). While unsustainable forestry has been a recognised issue in West Africa for some time (Blackett and Gardette, 2008; Wessels *et al*., 2013), the extensive clearance of recent years has arguably resulted from the excessive, and often illegal, harvesting of a single species synonymous with these woodlands – *Pterocarpus erinaceus*, or the African rosewood (CITES, 2015). This tree has long been important to local communities: its wood is ideal for construction and joinery, (Segla *et al*., 2014), its dried leaves are highly nutritious animal fodder (CITES, 2015), and it possesses various pharmaceutical qualities (Ouedraogo *et al*., 2006). However, in the last decade Chinese demand for *P. erinaceus* has grown exponentially, with its import value burgeoning from $12,000 in early 2009, to $180 million by the end of 2014 (CITES, 2015); this 'rapacious appetite' for rosewood (Chapman, 2016) has driven boom and bust cycles of extraction across West Africa, with levels of exploitation in different countries varying according to the safeguarding measures established and the extent of remaining stocks (CITES, 2015). Nigeria has recently found itself at the forefront of this unsustainable harvesting. Commercial rosewood logging began in Taraba State as recently as 2011 (Ahmed *et al*., 2016), but by the end of 2015 the country as a whole had already become the region’s largest exporter to China, accounting for 45% of its total imports (Aiyetan, 2016). This initiation and then rapid expansion of harvesting is visible in the outputs of Biomass Matching for CA 2; there are concentrated pockets of AGB loss within the area (*Fig. 4.5*c), much of which appears to have occurred between 2011 and 2016 (*Fig. 4.7*). Therefore, the analyses undertaken here arguably validate the reports of extensive woodland clearance in Taraba State (Ahmed *et al*, 2016; Aiyetan, 2016; Chapman, 2016; Ahmed and Oruonye, 2017), though the complexities associated with AGB change estimation from L-band RCS data (Mitchard *et al*., 2011; Ryan *et al*., 2012) mean the results better serve as a more relative indication of AGB loss. Furthermore, as CA 2 is only a representation of the areas of Taraba State vulnerable to disturbance, it is probable that lands surrounding major settlements (such as Jalingo and Bali) will have experienced even more dramatic clearance and degradation.

4.4.2 Woodland Degradation and Disappearance – is there a solution?

Unsustainable timber harvesting has been an enduring issue afflicting forests and woodlands across West Africa (Blackett and Gardette, 2008), facilitated by an array of factors which complicate attempts to address it. Indeed, though the clearance of entire woodlands of *P. erinaceus* is currently a major problem, there are fears that other endemic species could suffer a similar fate once rosewood stocks become suitably depleted, triggering vicious cycles of exploitation which could devastate West Africa’s dry forests and savannahs (CITES, 2015). Despite established timber regulations to protect particular species and fragile habitats, illegal harvesting often continues unabated (CITES, 2015), encouraged by severe deficiencies in management and resourcing (Franck and Hansen, 2014). In Taraba State, such regulations were reinforced in both 2007 and 2009 to stimulate greater general habitat protection, as well as within forest reserves (Ahmed *et al*., 2016); however, the relative absence of any formal monitoring or maintenance for such PAs (Burgess *et al*., 2005), coupled with endemic corruption, has rendered these policies largely ineffective, with such reserves largely incapable of protecting their habitats from anthropogenic disturbance (Ahmed and Oruonye, 2017). This emphasises the pivotal role of appropriate management and resourcing in deterring detrimental activities and ensuring strong PA performance (Leverington *et al*., 2010; Andrade and Rhodes, 2012; Laurance *et al*., 2012; Sassen *et al*., 2013; Tranquilli *et al*., 2014; Watson *et al*., 2014; Blackman *et al*., 2015), and it may be the most effective means of addressing unsustainable harvesting, not only in Taraba State, but across West Africa. The effectiveness of Gashaka-Gumti National Park when compared with CA 2 (*Fig. 4.5; 4.6*) could be partially explained by this: while its management and resourcing may be insufficient for a PA of its size (Chapman *et al*., 2004), it still receives greater protection than smaller PAs or unprotected lands in the state (Burgess *et al*., 2005; Oruonye and Abbas, 2011; Ahmed and Oruonye, 2017). Therefore, even small increases in the monitoring and maintenance afforded to vulnerable savannah woodlands could be critical in attempts to halt their current decline.

However, it is unlikely that the starkly contrasting trends in AGB change between Gashaka-Gumti and CA 2 (*Fig. 4.6*) are solely a product of differences in management and resourcing. Not only would this be consistent with earlier

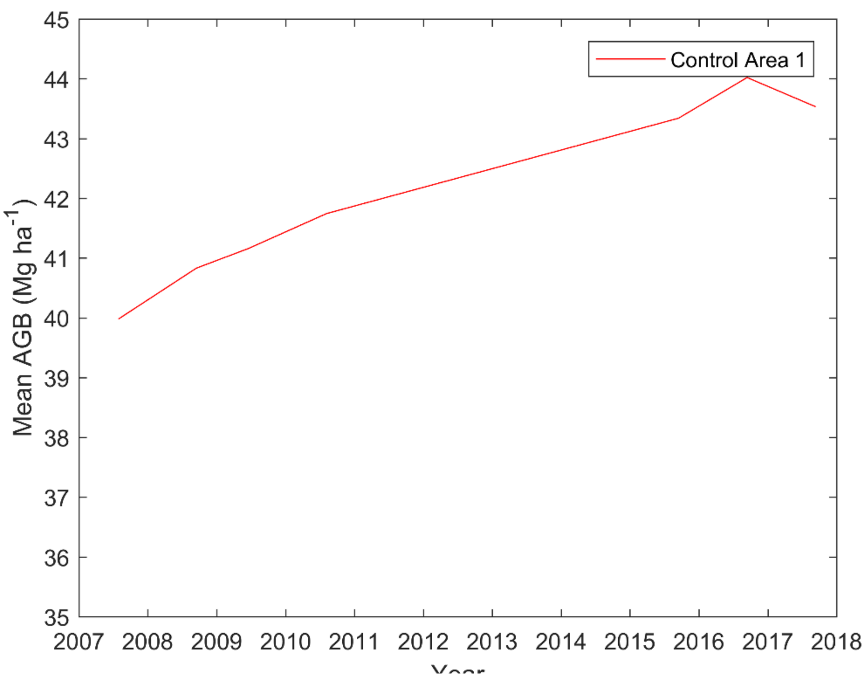


Fig. 4.8: Mean AGB Change 2007-2017 for (Very large) Control Area 1. This has been displayed alone to emphasise its steady increase in AGB over time.

discussions of various factors interacting to influence PA effectiveness, but it is strongly suggested by the products of Biomass Matching for CA 1: despite lacking any formal protection, the area experienced steady AGB increase between 2007 and 2016 (*Fig. 4.8*), and even greater per hectare AGB change than Gashaka-Gumti (*Table 4.1*). Indeed, the high elevation and steep slopes of CA 1 make it topographically inaccessible (*Table 4.1*), providing a natural deterrent against anthropogenic disturbance which may largely explain the observed conservation (and enhancement) of habitat within its artificial borders (Joppa and Pfaff, 2009; Pfaff *et al*., 2014; Bowker *et al*., 2017; Beresford *et al*., 2018). In addition to this remoteness, the absence of economically valuable species such as *P. erinaceus* from these high altitude forests and woodlands (Chapman *et al*., 2004; CITES, 2015) would further discourage commercial harvesting. It may therefore be postulated that the impressive performance of Gashaka-Gumti as a PA primarily results from both the resourcing it receives and its situation in the mountainous, eastern reaches of Taraba State. While this offers hope that similarly inaccessible areas in the state may be spared from the current wave of habitat degradation (Ahmed *et al*., 2016; Chapman, 2016; Aiyetan, 2016; Ahmed and Oruonye, 2017), it accentuates the challenges facing its lowland wooded areas, suggesting that without effective protection measures, loss of the state’s rosewood woodlands may be all but inevitable.

Conclusion

5.1 Summary of Findings

The novel Biomass Matching procedure developed by Hill *et al*. (in prep) may provide an excellent means of using SAR remote sensing data to detect both large-scale and subtle AGB changes in tropical ecosystems. Large-scale habitat changes displayed by optical remote sensing data (e.g. Google Earth 7) can often be confirmed by the AGB Change maps produced by Biomass Matching (*Fig. 3.1*; Appendix A), while synthetic validation approaches (*Fig. 3.3*; *Table 3.1*) demonstrate the procedure's ability to also detect more subtle AGB changes in an ecosystem. The ability of Biomass Matching to detect these changes is, however, contingent on the appropriate SAR data being used to study an ecosystem. L-band SAR is applicable to tropical drylands, as AGB levels here will rarely exceed 100 Mg ha^{-1} (Mitchard *et al*. 2009), but above this threshold the RCS signal sensitivity can be greatly reduced (Mermoz *et al*., 2015). Accurately predicting AGB change using Biomass Matching may however be far more challenging, because estimates are heavily dependent on the RCS-AGB relationship applied to the procedure. Although trends in AGB change for the Nigerian PAs are identical when using either Ryan *et al*. (2012)'s or the universal RCS-AGB relationship (*Fig. 3.4*), the AGB levels predicted for each year differ; this results in Ryan *et al*. (2012)'s regression almost consistently estimating greater per hectare AGB change for each PA between 2007 and 2017 (*Table 3.2*). Furthermore, these RCS-AGB relationships are heavily dependent on the data and methods used to develop them. The universal regression was developed using data which is far more applicable to this investigation, but with a less robust approach (Avitabile *et al*., 2016); that of Ryan *et al*. (2012) was calibrated using field data, making it specific to a their study site in Mozambique, but methodologically more sound. It must also be considered that RCS is not a 'direct' measure of AGB (Woodhouse *et al*., 2012), so no estimates will be completely accurate. Therefore, Biomass Matching may best be used to infer relative AGB change over time, and provide a more general indication of PA effectiveness.

In Nigerian drylands, PAs are more effective at both conserving and enhancing AGB levels than similar unprotected CAs. PAs of all size categories, and overall, experienced more positive AGB change 2007-2017 (*Table 3.3*; *Fig 3.5*), although differences between samples were not statistically significant at the 95% confidence interval ($p>0.05$). Limitations with the methodology and data interpretation – including the subjective creation of PAs as opposed to more robust ‘matching’ methods (e.g. Andam *et al*., 2008), and assumption of AGB loss resulting from adverse anthropogenic activities (Frost, 1999; Bond and Archibald, 2003; Nelson and Chomitz, 2011; Archibald *et al*., 2012) – may have influenced findings to some degree. However, these results support the growing body of literature advocating the importance of PAs in both tropical drylands (Carranza *et al*., 2014; Paiva *et al*., 2015; Ament and Cumming, 2016) and humid forests (Andam *et al*., 2008; Gaveau *et al*., 2009; Joppa and Pfaff, 2010; Nelson and Chomitz, 2011; Beresford *et al*., 2013; Cuenca *et al*., 2016; Bowker *et al*., 2017) for conservation purposes.

Discussions around the factors influencing PA effectiveness are incredibly complex: not only may a factor influence PA performance independently and through interactions with others, but its perceived importance may be biased by the datasets, methods and analyses employed by that particular investigation. In Nigerian drylands, accessibility – and particularly slope (*Fig. 3.11*) – emerged as a key determinant of PA effectiveness, both independently (*Table 3.5*; *Fig. 3.11*) and by virtue of its effect on other factors. For example, the level of protection assigned to a PA may have been heavily influenced by its accessibility (Joppa and Pfaff, 2009). However, the potential importance of other factors cannot be discounted, both those explicitly included in this study (such as age), and those not considered; the latter particularly refers to the management and resourcing a PA receives, as appropriate measures can contribute enormously to habitat conservation (Leverington *et al*., 2010; Andrade and Rhodes, 2012; Laurance *et al*., 2012; Sassen *et al*., 2013; Tranquilli *et al*., 2014; Watson *et al*., 2014; Blackman *et al*., 2015).

The outputs of Biomass Matching for (very large) CA 2 verify reports of extensive, unsustainable logging of Taraba State’s woodlands in recent years (*Table 4.1; Fig. 4.5; Fig. 4.6*). This has likely been driven by the excessive demand for *P. erinaceus* timber from China, a phenomenon which has devastated large swathes of West African savannah woodland (CITES, 2015; Ahmed *et al*., 2016; Aiyetan, 2016; Chapman, 2016). The encouraging performance of Gashaka-Gumti implies that, with appropriate management, PAs in Taraba State – and perhaps in drylands across the region – could be an effective means of preventing habitat clearance and degradation. However, the similarly strong performance of (very large) CA 1 suggests that inaccessibility may also be a crucial cause of its effectiveness. Therefore, while effective management is important for PAs in Taraba State (and across the drylands of West Africa as a whole) to succeed, the ability of more topographically accessible PAs to halt woodland clearance may be somewhat limited.

5.2 Recommendations for Future Research

This study has purposed to further our understanding of PAs in tropical dry forest and savannah ecosystems. Not only has it underpinned their critical role in habitat conservation efforts, but revealed consistencies in the factors influencing PA performance across tropical and extra-tropical regions. Importantly, the novel Biomass Matching approach has been established as an effective means of detecting AGB change, although its utility for change estimation may be limited to more relative inferences. Time and financial constraints limited some aspects of the study, and certain avenues of investigation were not possible; therefore, some recommendations for future research into tropical PAs are as follows:

- It would be useful to ascertain the accuracy of AGB changes estimated using RCS-AGB regressions developed from reference datasets such as that of Avitabile *et al*. (2016) for a set of study sites. A field-derived RCS-AGB relationships could be developed specific to these study sites, and estimates of AGB change from the two regressions could be compared.
- All subsequent investigations into West African dryland PAs should employ sophisticated ‘matching’ methods when assessing overall effectiveness; this objective approach will account for the non-random siting of PAs in landscapes and prevent potential spillover effects from over- or underestimating PA performance in relation to CAs, as well as ensuring comparability with studies employing the same method (Andam *et al*., 2008; Gaveau *et al*., 2009; Joppa and Pfaff, 2010; Nelson and Chomitz, 2011; Carranza *et al*., 2014; Blackman *et al*., 2015; Bowker *et al*., 2017).

- When considering the factors affecting PA performance, the broadest range possible should be included in descriptive and statistical analyses. A factor that should always be explicitly explored – if possible – is the management and resourcing received by PAs, as although it can constitute a host of quantitative and qualitative variables, it may be one of the most important determinants of PA effectiveness (Leverington *et al*., 2010; Andrade and Rhodes, 2012; Laurance *et al*., 2012; Sassen *et al*., 2013; Tranquilli *et al*., 2014; Watson *et al*., 2014; Blackman *et al*., 2015).
- Once P-band SAR data from the ESA's BIOMASS mission is available (ESA, 2015), this should be subjected to Biomass Matching to enable extensive studies of AGB change in dense tropical forest PAs. This could be particularly effective for detecting both subtle and large-scale AGB change (Mitchard *et al*., 2011; Ryan *et al*., 2012), giving robust indications as to their overall performance.

Appendices

Appendix A – Processing of L-band SAR data in preparation for Biomass Matching

The following details the steps taken in ArcMap 10.5.1 to prepare L-band SAR data (2007 – 2010 and 2015 – 2017) for each PA for Biomass Matching in MATLAB R2017a:

1. Appropriate data was first imported into a new ArcMap 'project'; this comprised of a PA's shapefile – downloaded from the WDPA (2018) – and radar scenes covering the shapefile's area for each year, imported as individual rasters (JAXA, 2018; *Fig. A.1*).

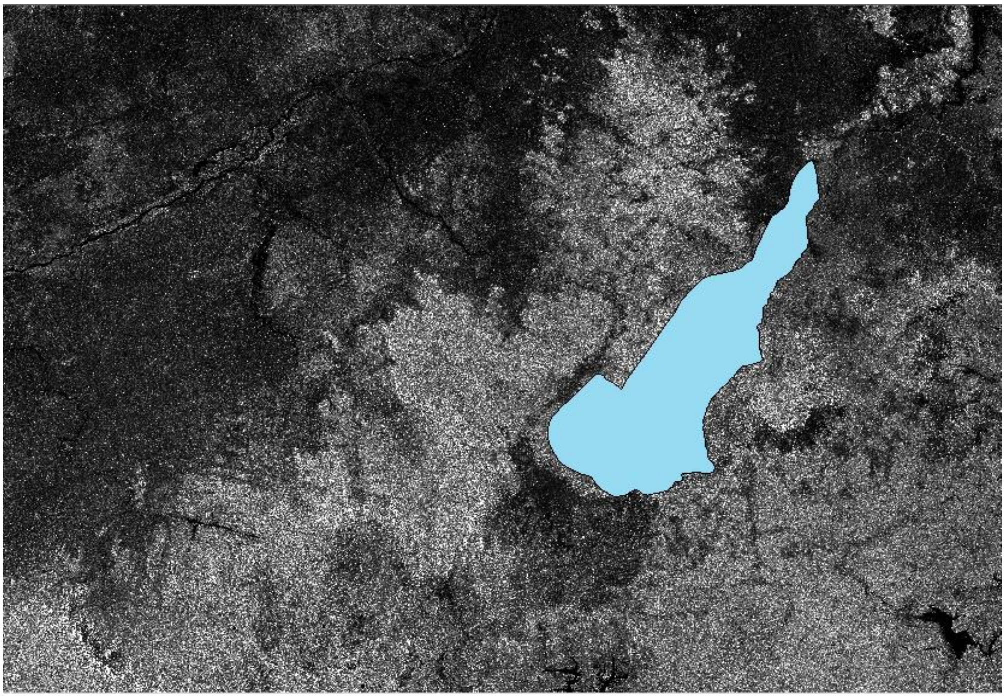


Fig. A.1: The shapefile for Gashaka-Gumti (shaded in blue) set against the sixteen individual radar scenes downloaded to encompass most of Taraba State, Nigeria.

2. If multiple rasters were required for each year, these were combined to produce mosaics by using the ‘Mosaic to New Raster’ tool, followed by the ‘Mosaic’ tool in the ArcToolbox. After this, the ‘Clip’ tool was used to extract the PA’s area from the each year’s mosaic (*Fig. A.2*), giving the raw data required for processing.

Fig. A.2: Gashaka-Gumti, extracted from raw L-band SAR data for 2017.

3. As the raw data was in the form of digital numbers, this needed to be converted to RCS values; using the ‘Raster Calculator’, the following equation made this conversion possible:

$$0.0000000050119 \times DN^2$$

where ‘DN’, or ‘Digital Number’, represents the clipped PA for a particular year (*Fig. A.3*). This produced new rasters for each year, with values for each pixel now corresponding to RCS.

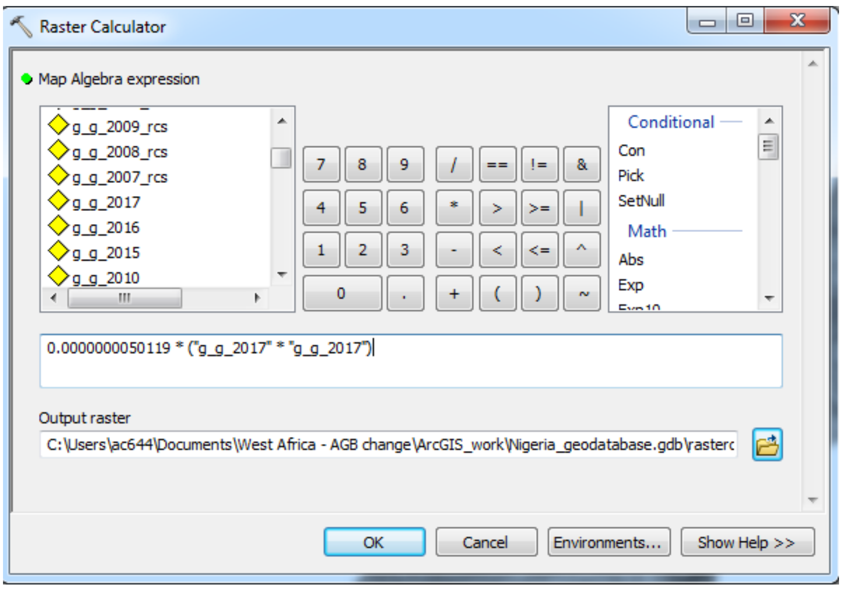
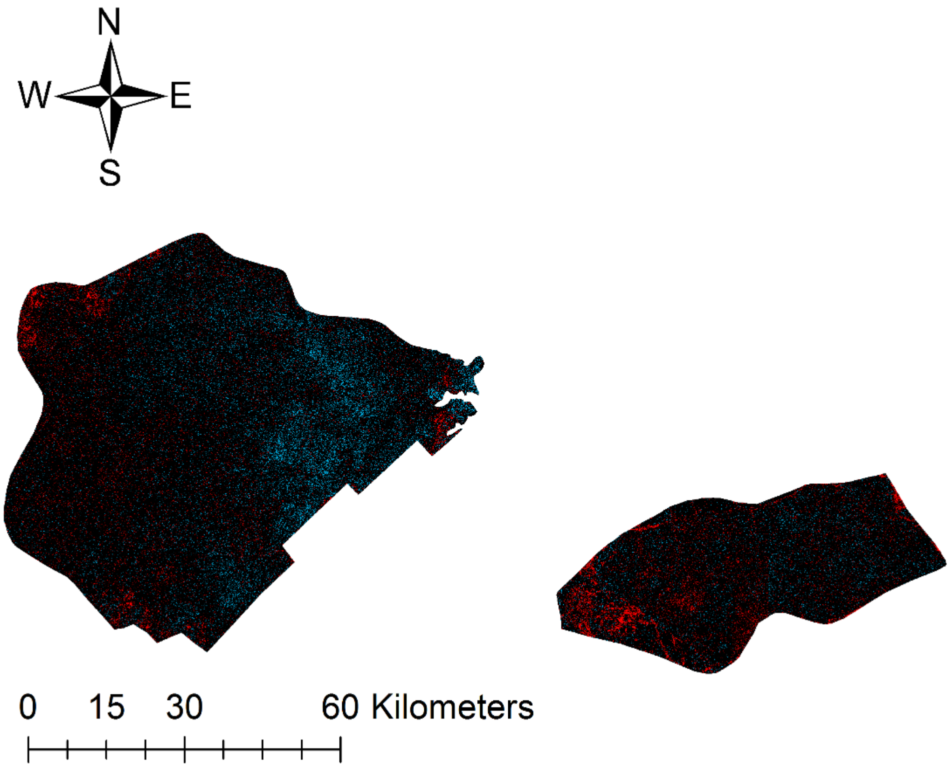
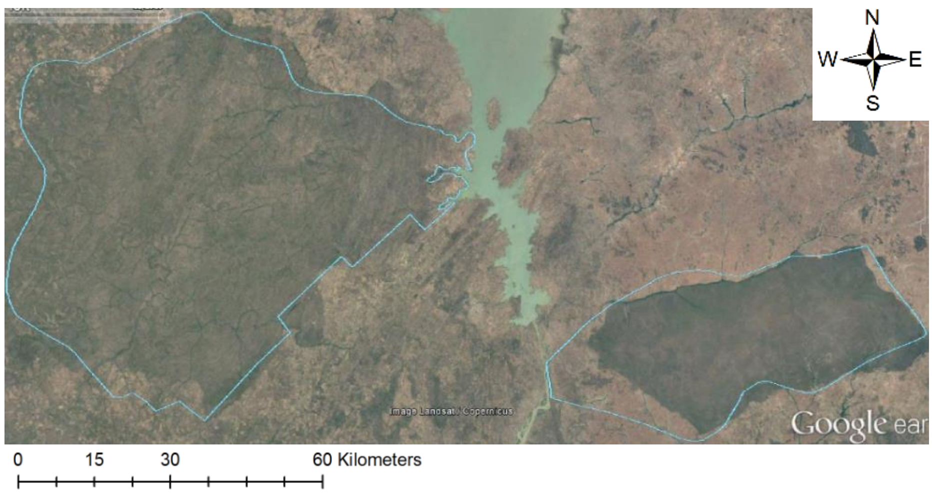


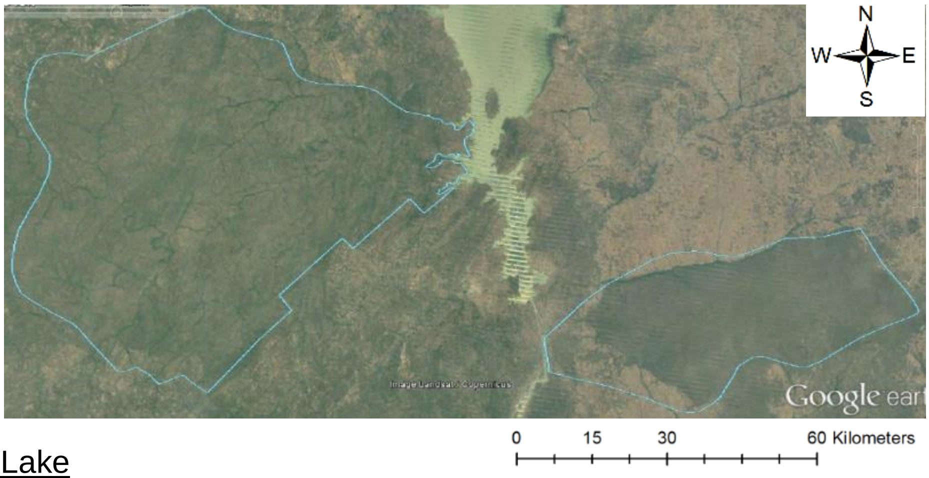
Fig. A.3: Using the ‘Raster Calculator’ to obtain RCS values for each PA for each year.

4. The RCS rasters were then combined into a stack by using the 'Composite bands' tool. From this, RCS data for each year for the PA could be exported from ArcMap as a '.tif' file, ready for Biomass Matching.

Appendix B – <u>Visual validation of AGB change in Kainji Lake and Upper Ogun</u>

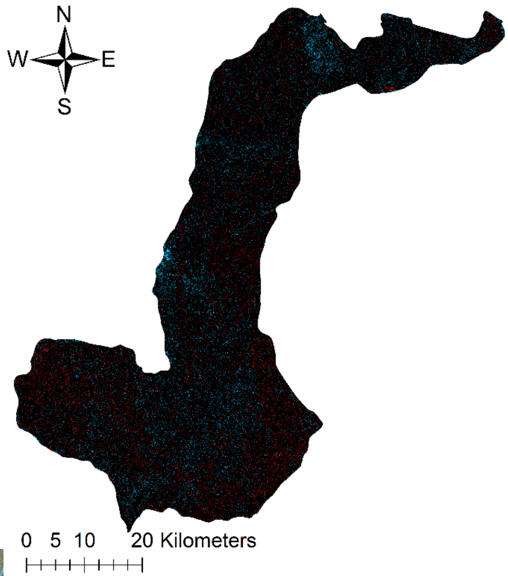


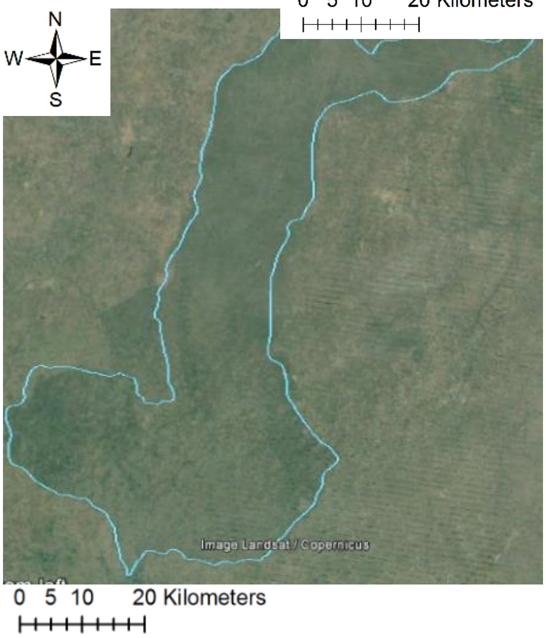


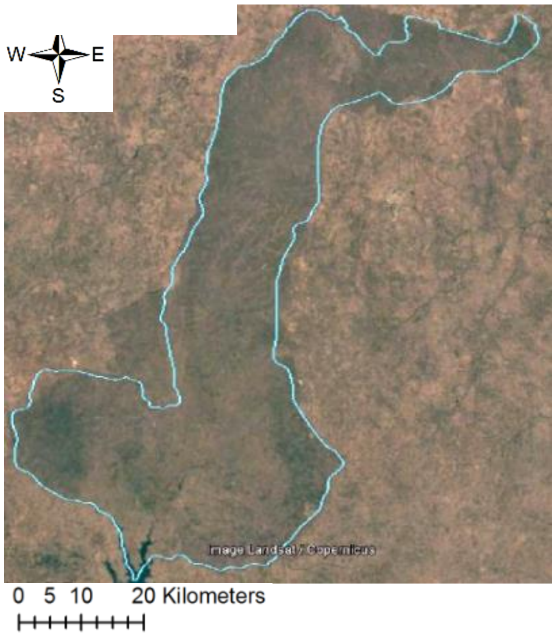


<u>Kainji Lake</u>

The PA can be clearly identified in Google Earth – definite boundaries for both 2007 (above) and 2016 (below). The Landsat is slightly patchy, but decreases in AGB identified by Biomass Matching on the west side of smaller subsection of the PA can arguably also be seen in Google Earth.







Upper Ogun

The PA is clearly visible in Google Earth, with defined boundaries which remain constant between 2007 (left) and 2016 (right). However, as incidences of AGB change within the PA are fairly sporadic, it is not particularly useful for validation purposes.

Appendix C – Outputs of multiple regression analysis for research question 3

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.669[a]	.448	.419	.9593561824	.448	15.419	1	19	.001

a. Predictors: (Constant), Mean slope (□)

b. Dependent Variable: Per ha AGB change (Mg/ha)

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	14.191	1	14.191	15.419	.001[b]
	Residual	17.487	19	.920		
	Total	31.678	20			

a. Dependent Variable: Per ha AGB change (Mg/ha)

b. Predictors: (Constant), Mean slope (□)

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.238	.326		.731	.473
	Mean slope (□)	.251	.064	.669	3.927	.001

a. Dependent Variable: Per ha AGB change (Mg/ha)

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics
						Tolerance
1	Spatial extent - Matlab /ha	.017[b]	.094	.926	.022	.957
	Age (years since establishment)	.329[b]	2.095	.051	.443	.999
	Mean elevation (m a.s.l)	-.024[b]	-.132	.896	-.031	.961
	Major settlements within buffer	-.041[b]	-.234	.818	-.055	1.000
	Road length within buffer (km)	-.074[b]	-.419	.680	-.098	.978

a. Dependent Variable: Per ha AGB change (Mg/ha)

b. Predictors in the Model: (Constant), Mean slope (□)

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